

**Ph.D. Thesis in Science and Technology for Electronic and
Telecommunication Engineering**

**Design and Development of ReMoVES
Platform for Motion and Cognitive
Rehabilitation**

Data processing for automatic performance evaluation

Matteo Morando

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Department of Naval, Electric, Electronic and
Telecommunications Engineering (DITEN)
Università degli Studi di Genova

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Abstract

Exergames have recently gained popularity and scientific reliability in the field of assistive computing technology for human well-being. The ReMoVES platform, developed by the author, provides motor and cognitive exergames to be performed by elderly or disabled people, in conjunction with traditional rehabilitation.

Data acquisition during the exercise takes place through Microsoft Kinect, Leap Motion and touchscreen monitor. The therapist is provided with feedback on patients' activity over time in order to assess their weakness and correct inaccurate movement attitudes.

This work describes the technical characteristics of the ReMoVES platform, designed to be used by multiple locations such as rehabilitation centers or the patient's home, while providing a centralized data collection server. The system includes 15 exergames, developed from scratch by the author, with the aim of promoting motor and cognitive activity through patient entertainment.

The ReMoVES platform differs from similar solutions for the automatic data processing features in support of the therapist. Three methods are presented: based on classic data analysis, on Support Vector Machine classification, and finally on Recurrent Neural Networks. The results describe how it is possible to discern patient gaming sessions with adequate performance from those with incorrect movements with an accuracy of up to 92%.

The system has been used with real patients and a data database is made available to the scientific community. The aim is to encourage the dissemination of such data to lay the foundations for a comparison between similar studies.

Contents

Contents	iv
1 Introduction	1
2 State of the Art	5
2.1 Exergames for rehabilitation	5
Existing solutions	7
2.2 Cognitive and upper limb	8
2.3 Hand Rehabilitation	9
2.4 Sit to Stand	10
2.5 Trunk and Balance Rehabilitation	12
2.6 Unilateral spatial neglect	12
2.7 Machine Learning in exergames	14
3 Materials	17
3.1 ReMoVES	17
3.2 Exergames	21
Breath Ball	25
Albert Test	27
Bisection Test	27
Apple Test	28
Owl Nest and Shelf Cans	29
Flappy Cloud	30
Equilibrium Paint	31
HotAir	31
Push Box	32
CityCar, Endless Zig and Wine Bottle	34
Floating Trap	34
3.3 Architecture	35
Client side	36
Server side	41
Web Interface	45
4 Methods	47
4.1 Method 1: Data Analysis	47
4.2 Method 2: Classification via SVM	50
Introduction to SVM	51
SVM for Exergames evaluation	62
Model tuning	64

Grid Search optimization	66
Session evaluation	69
4.3 Method 3: Classification with LSTM	70
5 Results	75
5.1 Clinical Trials	75
Participants	75
5.2 Database release	78
5.3 Method 1: Data Analysis	79
Upper Limb	79
Lower Limb	88
Sit to Stand	89
Balance Shift	94
Balance Control	97
Hand Movements	99
Cognitive	100
5.4 Method 2: SVM Classification	100
Push Box	101
Shelf Cans	105
5.5 Method 3: LSTM Classification	107
Equilibrium Paint	107
6 Conclusion	109
Discussion: database release	109
Discussion: SVM performance	109
Discussion: LSTM performance	110
A Appendix	111
Conference Papers	111
Journals	111
Chapter in book	112
Presenting at Conferences and Workshops	112
scientific acknowledgments and Awards	112
Bibliography	113

In the field of assistive computing technologies for human well-being, active exergames have recently gained large popularity and have proved scientific reliability, thus overcoming their original goal of mere entertainment. Referring to exergames as “the activity of playing video games that provide physical exercise” [1], scientific evidence has been reported dealing with positive results for the preservation and improvement of cognitive functions in elderly population [2]. At the same time, active exergames have acquired a precise position among the recommended rehabilitation methods when dealing with post-stroke patients [3].

In addition, the collection of data and information on patient activity during the exercise offers unforeseen opportunities, and it is mandatory to take full advantage of computer-aided technologies. During the exercise, the collection of data is the necessary feature to give the therapist the possibility of understanding the patient’s behavior, assessing his fatigue, and eventually correcting wrong attitudes such as compensation mechanisms. In this way, the physiatrist maintains control over the patient’s activity, follows progressions and improvements, and obtains the necessary basis for prescribing and adapting a personalized plan of care.

The present study takes place in this scenario and discloses the ReMoVES (REmote MONitoring Validation Engineering System) platform: it addresses the problem of continuity of care smartly and economically. It is based on state of the art technologies that offer innovative interfaces with serious games. Compared to commercial solutions that promote the activity at the player’s home, the video games presented in this work have been developed from scratch according to the indications of the clinical staff with specific medical purposes. ReMoVES can help patients with neurological, post-stroke, and orthopedic diseases in recovering physical, psychological, and social functions. This system is meant to improve the quality of life and accelerate the recovery process for patients, and also aims to rationalize and assist the workforce necessary to monitor and educate individual

[1]: Exergame. (2019), *Macmillan English Dictionary for Advanced Learners*

[3]: Lanctôt et al. (2019), ‘Canadian Stroke Best Practice Recommendations: Mood, Cognition and Fatigue following Stroke, update 2019’

patients in rehabilitation centers. This solution spins off from the European Project Rehab@Home (FP7 n.306113) and addresses in an innovative way the theme of user's participation in a technology conception as well as the universal access to technology at a broad public thanks to the possibility to spread the care and rehabilitation service at a low-cost [4].

The platform ReMoVES has been developed by the author during the Ph.D. research activity at the NUMIP Laboratory of Department of Naval, Electric, Electronic and Telecommunications Engineering (DITEN) - Università degli Studi di Genova, under the scientific supervision of Prof. Silvana Dellepiane. The aims of the present work are:

- ▶ introducing the technologies employed in ReMoVES platform;
- ▶ describing the capabilities of the system in delivering motor and cognitive exercises;
- ▶ proving reliability, user-friendliness, and engagement power;
- ▶ acquiring a broad set of data for each game session required for observing the patient activity during the game;
- ▶ proving the intelligibility of data in understanding user activity;
- ▶ proving the correlation between acquired data with computer-assisted technologies and traditional assessment tests;
- ▶ applying data analysis and machine learning techniques for performance evaluation during rehabilitation;
- ▶ publicly releasing a database called ReMoVES DB1 along with its annotation useful to interested researchers.

Chapter 2 presents state of the art in exergames rehabilitation, along with the interaction technologies used by systems similar to ReMoVES. Many scientific publications have turned to the analysis of the benefits of these tools in the field of rehabilitation. This chapter highlights the advantages of employing active exergames in the context of assistive computing technologies for human well-being. Nowadays, many rehabilitation structures are interested in introducing modern solutions to better support the patient both during the recovery phase and successively after the de-hospitalization. Current technologies range from the simple use of devices such as the Nintendo Wii Balance Board combined with

commercial video games, to ad hoc solutions that target different pathologies. ReMoVES fits in the latter case, offering exclusive and easy to use exergames based on interaction through Microsoft Kinect, Leap Motion, and Touchscreen.

Chapter 3 describes the hardware devices and the software architecture used by the ReMoVES platform. The system includes 15 exergames, which, through simple game dynamics, allow patients to interact –regardless of age– easily. The rehabilitation process can, therefore, be turned to a moment of entertainment for the patient. These activities adapt automatically to the patient thanks to a calibration phase and a real-time adjustment, to make the game progressively more appealing without discouraging the player. This chapter also includes a technical description of the infrastructure that enables the communication between devices dislocated in multiple rehabilitation centers (clients) and the central storage and processing system (server).

Chapter 4 introduces the data processing methods acquired during rehabilitation sessions through ReMoVES. Movement data and in-game events are recorded to reconstruct the patient's actions, and conduct analyzes retrospectively. Three methods have been developed for ReMoVES:

- ▶ Method 1: selection and data processing, visualization by means of graphs, summarization, and extraction of significant indicators for each exergame. This method provides the clinical staff with objective measurements of the patient's performance and his temporal evolution.
- ▶ Method 2: application of the supervised classification method based on "Support Vector Machine" for the automatic evaluation of game sessions. The datasets are based on the features defined by Method 1.
- ▶ Method 3: application of "Long short-term memory" neural networks for the automatic evaluation of exergames for motor rehabilitation. This technique involves a learning process based directly on time-series of raw data on the movement, without defining and manually selecting the features.

Chapter 5 gives the results of the employment of the methods presented in the previous chapter. Some exergames are reported as an example of these analyzes. When machine

learning methods are used, the results of the automatic performance evaluation models are provided. Clinical trials were conducted with real patients at “Centro di Riabilitazione, Gruppo Fides Genova, Italy”, “Ospedale San Martino Padiglione Maragliano, Genova, Italy” and “Fondazione Don Carlo Gnocchi, Marina di Massa, Italy”. Thanks to this study, a database was also publicly released containing raw data acquired during the testing phase at rehabilitation centers. This database, called ReMoVES DB1, is an innovation key brought by the present work. In fact, despite the strong scientific interest in this field, publications that provide the raw data acquired during the execution of exergames were not found. The lack of raw data related to exergame sessions consistently limits the development and the comparison between assistive computing technologies.

Finally, the conclusion, Section 6, comments on the results obtained and evaluates the performance of the data analysis methods. This chapter also constitutes an invitation to the scientific community to leverage the published database and the suggested processing methods, in order to establish the framework for research activities related to the use of exergames for rehabilitation and to lay the groundwork for a direct comparison with systems similar to ReMoVES.

2.1 Exergames for rehabilitation

Digital innovation that has involved many areas of daily life is impacting the field of motor and cognitive rehabilitation. In recent years the interest of some researchers in the use of video games in physiotherapy, occupational therapy, and cognitive rehabilitation has increased. Many physical therapies are based on repetition to achieve a range of movements or control over a specific muscle group. If this process is performed without any external encouragement, patients lose his motivation during therapy, and rehabilitation becomes slower and more frustrating [5]. The exergames can be used as a rehabilitation tool and keep the patient's interest high.

The commercial products in this area consists of video-game consoles, used with specific activities for physical exercise or the simulation of real sports; for instance, the Nintendo Wii is used in some centers as a rehabilitation device, to help patients recover more pleasantly. New tools have the potential to create stimulating environments, which supports the participants' motivation through the development of skills and activity-based techniques. The spread of exergames for rehabilitation is supported by the recent development of devices, even at low cost, for tracking patient movements.

Motion capture techniques are used in a wide range of applications ranging from digital animation for entertainment to biomechanical analysis for clinical and sports applications. The use of optical reflector marking systems is the most common technique [6] [7], although there are other technologies, such as inertial or electromagnetic ones. Despite their popularity, marker-based methods have several limitations: high-quality data collection requires a controlled environment, and the placement of markers on the body can take a long time [8] [9]. Numerous scientific publications have summarized the common deficiencies of marker-based techniques [10] [11] [12]. Alternative motion capture offers an

[5]: Annema et al. (2010), 'Videogames in therapy: a therapist's perspective'

[6]: Cappozzo et al. (1995), 'Position and orientation in space of bones during movement: anatomical frame definition and determination'

[13]: Zhang (2012), 'Microsoft kinect sensor and its effect'

1: The device emits an infrared artificial light. By measuring the time it takes for this light pulse to complete the device-object-device path (flight time, round-trip), the distance is estimated. The measurement is performed simultaneously on all the pixels of the reception sensor present on the device, instantly creating a depth map of the framed scene.

2: The device emits an artificial infrared light. Two stereo infrared sensors provide a disparity map to calculate a depth map of the surrounding environment. The software detects the human hand and provides information on its joints.

[14]: Vonstad et al. (2018), 'Classification of Movement Quality in A Weight-shifting Exercise.'

attractive solution to the problems associated with marker-based methods.

New devices have emerged from the gaming industry, such as Microsoft Kinect [13], which allows the interaction with video-games in real-time without the patient having to hold any controller. Furthermore, this peripheral is considerably less expensive than the usual complex multi-camera systems. Microsoft Kinect is a marker-less and 3D motion capture device that offers real-time tracking of the player's body. No specific clothing or other equipment is required as body tracking on time-of-flight camera¹ technology for measuring the distance between the device and the points of the surrounding environment. The software deals with extrapolating the shape of the human body from the depth map and providing spatial information on its joints. In a few years, this device has become the reference point of the scientific community for the development of platforms for motor rehabilitation.

Based on comparable technologies, the Leap Motion² peripheral has achieved similar success in the world of exergames and video-games interfaces tool. This device allows 3D tracking of the joints and capturing the subtle hand and finger movements while controlling a virtual environment that requires hand-arm coordination.

The diffusion of low-cost 3D motion capture peripherals has led to the appearance of many solutions for rehabilitation, with different target patients: Parkinson's, post-stroke, post-surgery recovery, or frail elderly. It is crucial to design specific exergames for each disease, while systems like Nintendo Wii and commercial games are inadequate. These solutions already on the market, which target healthy young people, usually cause difficulty and frustration, as they are too complicated or fast concerning the cognitive and motor conditions of disabled patients. Therefore, in recent years, ad-hoc exergames solutions have been developed in this field. As a direct consequence of the use of technological tools in rehabilitation, the clinical staff can access objective data and measures acquired during the training process. The scientific community is focused on the implementation of algorithms to assess the motion quality [14], measure the player's performance, and detect erroneous movements.

Existing solutions

Traditionally, a great portion of physical therapy and rehabilitation assessment is based on a clinician's observation and judgment. Sensor and computing technology that can be used for motion capture, performance assessment, and Range of Motion (ROM) measurements have advanced drastically in the past few years.

Since 2011 [15] a fundamental role has been assumed by the Microsoft Kinect device [16] [17]: the easy availability on the market, the low cost and the monitoring without markers of the human body have attracted the attention of the scientific community, overcoming its original purpose of pure entertainment tool.

By developing game-based rehabilitation tools that are tailored to the therapy goals of different patient categories, it is possible to provide the clinician with more meaningful performance data. Over the years, an ever-increasing number of studies have focused on applying Microsoft Kinect in physical therapy. Google Scholar has indexed 512, 587, 608, 696 publications in 2015, 2016, 2017, and 2018 respectively, which have mentioned both "Kinect" and "rehabilitation" keywords, proving that this device is having a strong technical and practical impact in the physical therapy. Studies have focused in more detail on post-stroke recovery [18] [19], Parkinson assessment [20] [21] or orthopedic rehabilitation [22]. The exergames based on Microsoft Kinect have a significant field of application in assistive technologies for the elderly, such as for fall risk reduction [23] [24], to improve physical performances, and reverse the deterioration process in frail and pre-frail elderly. Microsoft Kinect is suitable for measuring full-body movements with adequate performance compared to traditional motion capture systems [25] [26].

Comparable popularity was reached by Leap Motion: it is a relatively recent optoelectronic system for capturing the motion of hands to control a virtual environment. Differently from existing solutions, it tracks the subtle movements of fingers with infrared stereo cameras without wearing glows or markers. The commercial success of the device lies in its simplicity, in its low cost, and the ability to detect small changes in hand / finger positions with high precision [27]. Leap Motion has been the subject of studies and practical

[15]: Lange et al. (2011), 'Development and evaluation of low cost game-based balance rehabilitation tool using the Microsoft Kinect sensor'

[18]: Dash et al. (2019), 'Kinect-assisted performance-sensitive upper limb exercise platform for post-stroke survivors'

[23]: Garcia et al. (2012), 'Exergames for the elderly: Towards an embedded Kinect-based clinical test of falls risk.'

[27]: Guna et al. (2014), 'An analysis of the precision and reliability of the leap motion sensor and its suitability for static and dynamic tracking'

[31]: Li et al. (2017), 'Hand gesture recognition for post-stroke rehabilitation using leap motion'

applications that have exploited the free-hand interaction function of the device [28] [29] [30].

In [31] the problem of residential rehabilitation of stroke patients in a context of shortages of medical resources is addressed. The activity without professional guidance or without the possibility of monitoring the progress of stroke patients by the therapist may lead to additional harm or deteriorate rehabilitation progress. To solve this problem, they developed a hand gesture recognition algorithm devoted to monitoring up to seven gestures during home-based rehabilitation of post-stroke patients. Additional publications report the application of Leap Motion as an interface for exergames with different purposes, although the most common use is for the rehabilitation of post-acute post-stroke elderly [32]. Still, the applications extend to traditional support for injury recovery or in video-games for children or adolescents for motor and cognitive rehabilitation [33] [34].

2.2 Cognitive and upper limb

Due to age or neurological diseases, weakness is a major limiting factor related to upper limb movements. The reduction in torque generation is reported at the level of the elbow, shoulder, fingers, and thumb, which worsen due to prolonged physical inactivity.

In this context, strength training associated with task-oriented training can intensify the rehabilitation and reinforcement of the upper limbs [35].

[35]: Silva et al. (2015), 'Strength training associated with task-oriented training to enhance upper-limb motor function in elderly patients with mild impairment after stroke: a randomized controlled trial'

By design, exergames turn very appropriate to this aim, as they require the patient to produce physical movements in order to complete a task-oriented exercise in response to visual cues [36]. In the meantime, they are able to improve patient engagement and train multiple cognitive processes simultaneously [37].

In addition to cases of psychiatric and neurological diseases, cognitive abilities inevitably decline in the healthy elderly population, thus leading to a severe social and economic impact.

The study of [38] suggests that physical exercise can produce cognitive improvements (associated with an increase in hippocampal volume) in accordance with the study [39] about the increased levels of Brain-derived neurotrophic factor (BDNF) in response to exercise.

A meta-analysis study [2] proves that both a healthy elderly population and patients with neurocognitive impairments have benefited from exergames that combine physical activity and cognitive tasks. Even though no significant effects on global cognition has been observed, positive outcome has been proved for executive functions (by improving inhibitory control and cognitive flexibility), attentional processing, and visuospatial skills.

In order to design an enjoyable and safe gaming experience for elderly users, several age-related requirements need to be considered [40]:

- ▶ target audience's lack of previous gaming experience: devices such a Microsoft Kinect enable users to control and naturally interact with exergames without the need to physically touch a game controller or object of any kind. Microsoft Kinect achieves this through a natural user interface by tracking the user's body movement;
- ▶ exergames should focus on simple interaction mechanism while complex and decorative graphics should be kept to the minimum;
- ▶ the exergames should avoid frustration and foster an enjoyable player experience: when motor skills of the user are reduced, a preventive calibration phase allows the patient to complete the game task even with a limited ROM.

2.3 Hand Rehabilitation

Hands and fingers play an essential role in human life. With their motion under a delicate control, hands and fingers are involved in almost all daily activities. Fingers also represent the most intense source of tactile feedback in the human body since they are the fullest areas of nerve endings [41]. The importance of hand and finger use can be easily understood by exploring the human brain. One of the most significant regions of the cerebral cortex is dedicated only to controlling,

[38]: Erickson et al. (2011), 'Exercise training increases size of hippocampus and improves memory'

[2]: Stanmore et al. (2017), 'The effect of active video games on cognitive functioning in clinical and non-clinical populations: a meta-analysis of randomized controlled trials'

[40]: Gerling et al. (2010), 'Exergame design for elderly users: the case study of SilverBalance'

[41]: Wallace et al. (1975), 'Variations in the nerves of the thumb and index finger'

[42]: Johnson (1998), 'Cerebral organization of motor imagery: contralateral control of grip selection in mentally represented prehension'

[43]: Skala Kavanagh et al. (2011), 'Computer supported thermography monitoring of hand strength evaluation by electronic dynamometer in rheumatoid arthritis—a pilot study'

[50]: Bohannon (1995), 'Sit-to-stand test for measuring performance of lower extremity muscles'

receiving, and processing sensations from hands and fingers [42]. The human hand consists of 27 bones, 27 joints, more than 120 ligaments, 34 muscles, 48 nerves, and 30 arteries. Due to the complexity of the anatomical system and the extensive use during life, the hand is subject to injuries and diseases.

In the case of hand motion disabilities, adequate rehabilitation is needed to increase the patient's quality of life. The rehabilitation commonly includes physical therapy, and if performed appropriately and frequently, it can help to regain partial or full functionality of hand/fingers. There are three types of exercise used in rehabilitation for hand motion disabilities:

- ▶ exercises to improve range of motion;
- ▶ strengthening exercises;
- ▶ aerobic or endurance exercises.

Lots of different sensory devices are used for hand/finger motion therapy, such as grip force measurement devices [43], finger pinch force sensors [44], VR gloves and exoskeleton systems [45], [46], [47], [48]. The importance of monitoring for the effectiveness of rehabilitation treatment is well recognized and represents the foundation of evidence-based health care [49].

However, many devices do not satisfy the requirements necessary for hand rehabilitation contexts –such as in the home without the supervision of technical or clinical personnel– in which low-cost and easy-to-use solutions are to be employed. For this goal, the Leap Motion can be deployed.

2.4 Sit to Stand

Sit to Stand (STS) is a well-known assessment test whose relevance in estimating lower limb strength is widely recognized [50]. Many studies discuss its effectiveness as an indicator of leg weakness and related falling risk in elderly and disabled people [51]. In addition to assessment, STS has been recently proved to be a task-oriented, strength-reinforcing exercise [52] [53] [54] [55]. For instance, in hemiparetic patients who can adopt a compensatory movement and bear less weight on the impaired limb [56], a strategy for different positioning

of the foot during STS allows targeted muscle strengthening [57] [58] [59] [60].

The importance of this test has given rise to numerous studies that implement new technologies such as wearable sensors or baropodometer board. Their primary purpose is to evaluate appropriate metrics for quantitative analysis, to allow data collection in case of repetitive uses, and to classify phases in each STS cycle. Inappropriate movements or risky situations must be identified and stopped.

The Microsoft Kinect is employed in the context of the improved STS with the support of new technologies: the development of appropriate exergames allows to guide the patient to conduct the exercise correctly and improves engagement thanks to stimuli and visual feedback. The primary purpose is to collect relevant data to explain specific movements during the game session, for example, to compare disabled patients with the typical performance of healthy subjects, detect improvements over time and find incorrect compensation movements. A large amount of data and signals is collected and analyzed, even by adopting deep learning techniques. To this purpose, the evaluation phase must be carried out taking into account the specific situation of the patient concerning his disabilities and physical conditions to have an individualized interpretation. Specifically, some critical positions and movements of the body joints are analyzed during the ascending and descending phases to assess the patient's actual status and attitude. During the STS exercise, healthy subjects perform symmetrical movements of critical joints such as shoulders and hips, preserve a straight position, and move the center of mass along the vertical axis. As a result, the imaginary line that crosses the shoulder joints is horizontal and positioned on the coronal plane, as well as that passing through the hips. Wrong movements are due both to specific disabilities and compensation strategies. They can be detected and explained based on the patient's diagnosis. The mitigation of erroneous movements or the increase in performance measured as an increase in the number of STS cycles in a given period of time is the result of effective rehabilitation treatment. Sensor-based technology systems and exergames allow monitoring and comparison with standard evaluation metrics (e.g., Tinetti Index [61]). Moreover, the exergames dedicated to the STS provide a fun component that stimulates the patient to adopt correct

[57]: Kim et al. (2015), 'Repetitive sit-to-stand training with the step-foot position on the non-paretic side, and its effects on the balance and foot pressure of chronic stroke subjects'

movements avoiding compensation strategies and improving their physical abilities.

2.5 Trunk and Balance Rehabilitation

[62]: Deutsch et al. (2009), 'Wii-based compared to standard of care balance and mobility rehabilitation for two individuals post-stroke'

[63]: Byrne et al. (2012), 'The effect of a three-week Wii Fit™ balance training program on dynamic balance in healthy young adults'

[66]: Lange et al. (2010), 'Development of an interactive rehabilitation game using the Nintendo WiiFit Balance Board for people with neurological injury'

[68]: Clark et al. (2012), 'Validity of the Microsoft Kinect for assessment of postural control'

Commercial game consoles, like the Nintendo Wii paired with Wii Balance Board, have recently gained a lot of interest in the context of physical therapy [62]. Numerous case studies showed that video games have the potential to be strong motivators for engaging in physical activity and highlighted potential employment in the field of balance rehabilitation following stroke [63], spinal cord injury [64], or fall prevention in the frail elderly [65].

However, currently available commercial games may not be suitable for the controlled and targeted exercise required for therapy. Usability studies have found that some commercially available games provide negative auditory and visual feedback during therapeutic activities [66]. These observations demonstrate the importance of designing specific games for rehabilitation, an approach that has been studied by many recent researchers [67]. However, the limitations of motion detection technology in commercial video games have been a challenge to achieve this goal. The Nintendo Wii Balance is a tool with an excellent precision versus cost ratio, but alternative solutions for estimating the Center of Mass (CoM) via Microsoft Kinect have been explored [68]. The advantages of using Microsoft Kinect for balancing exercises are:

- ▶ use a device already implemented in other exergames for other types of rehabilitation;
- ▶ does not require additional peripherals such as the Wii Balance Board to estimate the CoM;
- ▶ complete tracking of the user's body to evaluate movements in a more comprehensive way.

2.6 Unilateral spatial neglect

Patients suffering from the neuropsychological syndrome of unilateral spatial neglect (USN) fail to orient, report, or respond to stimuli in contralesional space after a cerebral stroke. Since it is not caused by primary sensory or motor

dysfunction, USN is considered a higher-order disorder [69]. Specific neuro-rehabilitation is then required, helping the re-acquisition of the functional ability and a better quality of life, along with appropriate tests to evaluate the disorder recovery. Understanding USN is crucial because of its functional implications [70] and impact on rehabilitation outcomes [71]. Indeed, its effects can persist long after the occurrence of stroke [72].

In order to assess not only the type but also the severity of neglect, doctors employ a variety of tests. Perhaps one of the most-used and quickest is the line bisection. In this test, three lines a few inches long is drawn on a piece of paper, and the patient is then asked to dissect each line at the midpoint [73]. Patients exhibiting, for example, left-sided neglect, will present a rightward deviation of the line's actual midpoint.

Another widely used test is the Albert Test. Here a patient is presented with a piece of paper that has various lines scattered across it and is asked to mark each of the lines. Patients who exhibit left-sided neglect will completely ignore all lines on the left side of the paper [74].

Moreover, it has been argued that there are different types of neglect. Allocentric neglect was associated with damage to posterior cortical regions (posterior superior temporal sulcus, angular, middle temporal, and middle occipital gyri). In contrast, egocentric neglect was associated with more anterior cortical damage (middle frontal, postcentral, supra-marginal, and superior temporal gyri) and damage within subcortical structures. Damage to intraparietal sulcus and the temporoparietal junction was associated with both forms of neglect [75]. An Italian standardization of the Apples Cancellation Test is proposed in [76]: it is a new instrument useful to evaluate both egocentric and allocentric forms of neglect.

The administration of the aforementioned tests, although simple, requires a work of counting and evaluation by the therapist. From these well-known paper-and-pencil tasks to the diagnosis and quantitative assessment of unilateral spatial neglect, a computerized version adopting touch-screen technology can be developed. The computer-based paradigm consisted of a visuo-motor spatial exploratory task: the subjects were instructed to touch the target on the computer screen. The time of occurrence and the spatial coordinates of

[70]: Jehkonen et al. (2000), 'Visual neglect as a predictor of functional outcome one year after stroke'

[76]: Mancuso et al. (2015), 'Italian standardization of the apples cancellation test'

each touch event is measured and forwarded the data to the computer for storage and analysis. The scoring of the test is automatically evaluated by the computer system, together with further information useful to clinical staff, usually not available in the paper-and-pencil version.

2.7 Machine Learning in exergames

The state of the art of Machine Learning (ML) techniques applied to exergames for motor or cognitive rehabilitation is still in an exploratory phase. The scientific literature mainly focuses on the recognition of gestures during the execution of the motor activity. In [77], ML is used for gesture evaluation of yoga. In this case, a series of exercises –conducted by teachers of this discipline– was recorded by instructors to build the training set. The system has identified multiple classes of gestures. After that stage, the yoga class students repeated the yoga exercises in front of one tracked with Microsoft Kinect, and the system automatically detected whether the movements were correct or not. In this study, the people were people aged 18 or over with the exclusion of people with cognitive or motor disabilities who were not healthy enough to participate in yoga postures and that the training set gestures were predetermined and equal for all participants (not customized).

[77]: Pullen et al. (2018), ‘Machine learning gesture analysis of yoga for exergame development’

An application to improve the quality of rehabilitation sessions in the clinic or at home, allowing data collection to be able to track patient training progress is described in [78]. In [79], two ML approaches are compared to evaluate patient performance during rehabilitation: Dynamic Time Warping (DTW) and Hidden Markov Model (HMM). The first is a technique for aligning two-time series that can vary in speed and measure the similarity between them (minimum Euclidean distance). It is mainly used for speech recognition but also gesture recognition due to the similarities between the two domains (temporal and spatial). The second method, on the other hand, is a stochastic model that considers an observed signal as the result of the transition of a system between different determined states, each of which has a probability that a particular symbol can be observed. Once trained to optimize its parameters, the HMM can be used to

[78]: Duarte et al. (2014), ‘KSGphysio-Kinect serious game for physiotherapy’

calculate the likelihood that the given sequence of observations (trajectories of movement) must be generated by the same process.

Another type of automatic learning approach to gesture recognition is Support Vector Machine (SVM). In [80], the researchers used Motion Captures (with 43 optical markers distributed over the body) to trace movement and SVM to predict 21 types of activities such as jumping, running, or standing. The average precision in this experiment is 84%. Furthermore, [81] uses Microsoft Kinect V2 and SVM to perform a 3-class classification for the subject as either “healthy”, “mildly impaired” or “moderately impaired” with the accuracy of 83%. This study turns out to be one of the few articles that address the classification based on the evaluation of movement quality, rather than on the mere identification of gestures. It is therefore considered a valid benchmark for comparison with the present study, where the data collected concern patients who, due to their disabilities, sometimes fail to perform complete gestures or do so with performances not comparable to healthy subjects.

[80]: Wang et al. (2009), ‘Recognition of human actions using motion capture data and support vector machine’

[81]: Dehbandi et al. (2016), ‘Using data from the Microsoft Kinect 2 to quantify upper limb behavior: a feasibility study’

3.1 ReMoVES

The ReMoVES system was developed as a data collection tool and platform for the present scientific research. This activity was carried out as a research branch in the healthcare field of the NUMIP Lab of the Department of Naval, Electrical, Electronics, and Telecommunications Engineering (DITEN) of Università degli Studi di Genova [82]. ReMoVES is a flexible platform that provides a set of services to support the motor and cognitive recovery through exergames carried out predominantly using Microsoft Kinect, Leap Motion, or touchscreen.

ReMoVES differentiates from existing solutions by being an auxiliary tool to provide therapists with objective rehabilitation data even when they cannot directly supervise their patients, such as during unattended use at their home, including automated data processing techniques [83] [84].

The purpose of this chapter is to describe the features of the ReMoVES platform. The technical development was entirely entrusted to the author, who was responsible for designing the architecture, the exergames and the data processing methods. ReMoVES is inspired by the prototype developed during the Rehab@Home project (founded by the European Union Seventh Framework Programme under grant agreement n°306113), where the NUMIP laboratory took part as a scientific partner. However, ReMoVES is configured as a technically different project: it was developed from scratch by the author to be lighter, modular and integrate more advanced data processing tools.

These improvements are made possible by the architecture with which ReMoVES was conceived from the early stages of development: a “multi-client to one server” organization allows you to collect and access information from different locations: it is designed to be used both in rehabilitation centers with the help of clinical staff and independently at the patient’s home after hospitalization.

[82]: Ferrara et al. (2017), ‘ReMoVES Remote Monitoring Validation Engineering System: New Way of Care’

[83]: Morando et al. (2018), ‘Definition of motion and biophysical indicators for home-based rehabilitation through serious games’

The idea behind the proposed system consists of providing a personal rehabilitation program that can be performed at home by the patient, while the therapist can track the performances and effectiveness of the training from any Internet-connected device. Among others, the monitoring of eventual compensation movements allows the evaluation of whether an exercise is accomplished correctly. In detail, the built-in algorithms aim to provide a clear and concise report to the therapist, in order to facilitate the interpretation of the evolution of therapy.

The ReMoVES platform employs off-the-shelf devices for motion tracking and biophysical data acquisition, which are activated during the execution of functional exercises. On the back-end, a server infrastructure delivers web-services and data processing methods. The ReMoVES platform deploys the following technologies.

Exergames are digital games that have been developed from scratch for the present scientific research. The system currently includes 15 different activities 3.2: they encourage the patient to carry out functional exercises autonomously along with the traditional motion rehabilitation. The creation of these activities involved different processes, technologies, and specialists. It is necessary to pay particular attention to the specifications provided by physiotherapists and physiatrists, who share their skills to define the requirements and parameters of the game. The interface was designed using the Unity platform ¹, which is a popular graphic engine used for the development of games and virtual reality applications. C# is the language that was used to write ReMoVES exergames. All the graphical resources in 2D and 3D format have been downloaded from different sources online with a Creative Commons license ². The whole set of games shares a core library that was developed to allow easy and straightforward communication with the Application Programming Interfaces (APIs) exposed by the cloud back-end that will be presented later.

1: Unity is a cross-platform game engine developed by Unity Technologies. <https://unity.com>

2: Pixabay.com is a website for sharing photos, illustrations, and vector graphics. All files can be used without attribution requirement and also for commercial aim. <https://pixabay.com>

Microsoft Kinect V2 is a motion-sensing input device based a Time-of-Flight camera to build a depth map of the environment. It can simultaneously 3D-track up to 25 fundamental joints (Fig. 3.1) of the framed human body. It offers a wide field of view (70×60 degrees) and

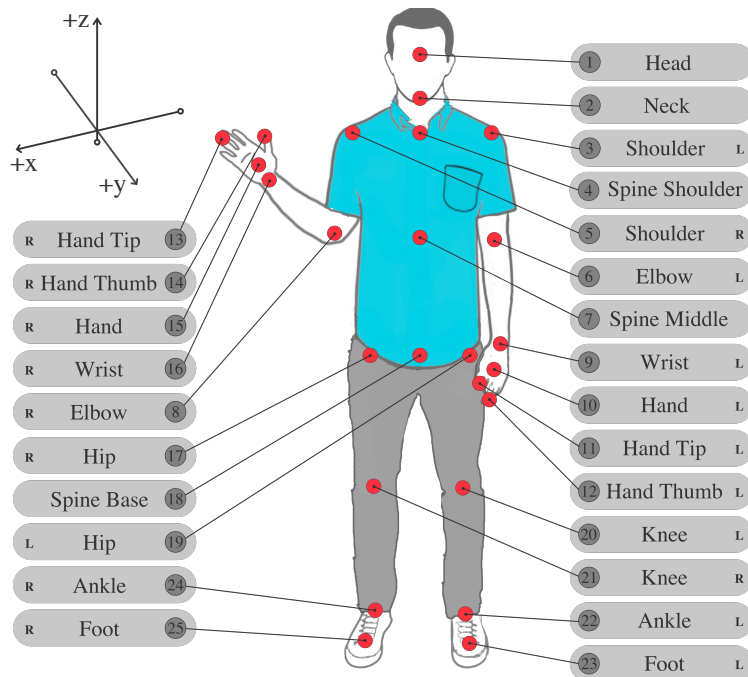


Figure 3.1: Skeleton joints tracked by the Microsoft Kinect sensor. The skeleton is composed of 3D coordinates for each of its 25 joints.

recognition up to 4.5m from the device [85]. Several studies have demonstrated that Microsoft Kinect V2 can validly obtain spatiotemporal parameters [86] [87]. The interface configuration between Microsoft Kinect V2 and the Unity engine is straightforward since the manufacturer provides the Software Development Kit (SDK) and an add-on for Unity. Developers can easily access the positions and orientations of body joints for direct use in the virtual environment of exergame.

Leap Motion is explicitly aimed at the recognition of hand gestures and calculates the position of the fingertips and the orientation of the hand (Fig. 3.2). Its area of interaction is limited to a hemisphere with a radius 0.60 m around the device, with a theoretical accuracy of 0.01 mm according to the manufacturer (or 0.7 mm under real conditions as measured by [88]). Examples of clinical studies that have used the Leap Motion controller are [30] [28]. The manufacturer provides an Assets for Unity package that allows effortless integration with this development engine.

Touchscreen (optional) for interacting with the subset of exergames for cognitive rehabilitation. The monitor is positioned on a table with an angle to the plane of a few degrees (10 degrees is the minimum tilt of the

[86]: Geerse et al. (2015), 'Kinematic validation of a multi-Kinect v2 instrumented 10-meter walkway for quantitative gait assessments'

[88]: Weichert et al. (2013), 'Analysis of the accuracy and robustness of the leap motion controller'

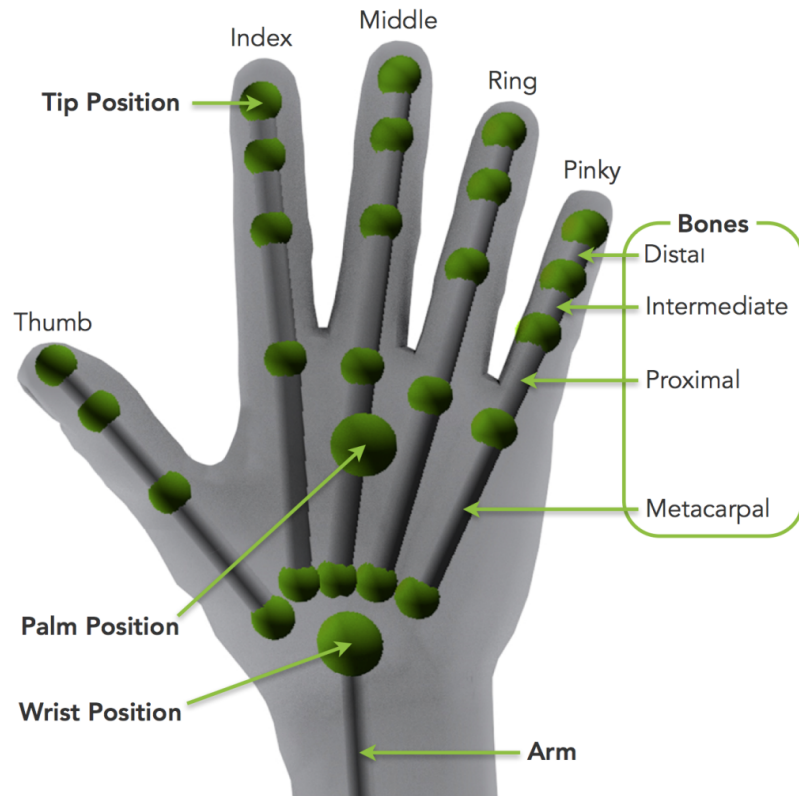


Figure 3.2: Skeletal tracking provided by the Leap Motion controller. Every tracked entity in the Leap Motion interaction space falls within a hierarchy that starts with the hand and ends at the individual bones.

product used). The cognitive exergames present in the ReMoVES platform are a digital reinterpretation of some gold-standard tests administered on paper to patients. The interaction through a touchscreen monitor allows a more complete collection of data. The normal test procedure involves the administrator taking notes on a limited set of information. The software support, on the other hand, collects auxiliary data such as interaction speed and methods / strategies used by the patient to complete the test. The touchscreen is not required for exergames for motor rehabilitation and is therefore optional.

Microsoft Band 2 (optional) is a physiological sensor that collects signals to measure patient involvement during the rehabilitation program: heart rate and electrodermal activity. It also includes a wide range of additional integrated sensors: accelerometer, gyroscope, barometer, GPS, skin temperature sensor, ambient light, and ultraviolet sensor (Fig. 3.3). Microsoft Band 2 offers the opportunity to collect data in real-time continuously for at least 4 hours without recharging [89]. For reasons related to the fact that Microsoft Band has been discontinued in the market, this device is no longer a re-

[89]: Al-Naffakh et al. (2016), 'Activity Recognition using wearable computing'

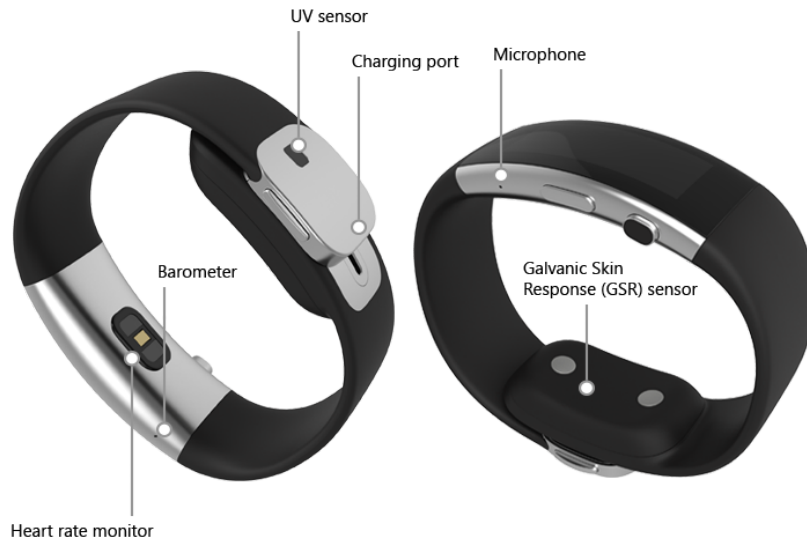


Figure 3.3: The Microsoft Band 2 includes multiple sensors: optical heart rate monitor, galvanic-skin response, accelerometer, gyroscope, barometer, GPS, skin temperature sensor, and UV sensor.

quirement of the ReMoVES platform and is, therefore, optional.

Back-end server was developed using state-of-the-art software tools to provide scalable and secure data processing and storage. It exposes software interfaces for user authentication and archiving of data coming from activity sessions carried out by multiple remote locations (rehabilitation centers, hospitals, or patients' homes). The data is stored on a Linux server relying on a MySQL relational database: it consists of tables for user supervision, session schedule, and archiving of exergames data. Acquisition data at a frequency of 10Hz allows a complete post-movement reconstruction of the in-game events. Conclusively, this component runs the data processing algorithms and provides the interface for displaying the results, also in graphic mode, for the clinical staff.

3.2 Exergames

Training activities through the ReMoVES platform are used together with the traditional rehabilitation program. The therapist can choose among a catalog of games, the most useful for the patients, based on their illness and level of disability.

The system currently includes 15 different exergames that can be modified based on level parameters, duration, range of motion, speed, or others. These activities adjust automatically

to the patient thanks to a calibration phase and a real-time tuning: for instance, the rate increases progressively until the patient experience critical difficulty.

The design of the exergames involved the clinical staff. In particular, the creative process aimed at the mere entertainment of the patient, including the graphic aspect and the methods of interaction, were entrusted in the first phase to the author; instead, the aspects directly related to movement and difficulty of exercise have been suggested by the therapist's experience. The exergames are complementary to traditional rehabilitation with similar movements, but the purpose with which they were developed is to entertain the patient and facilitate data collection. ReMoVES is therefore configured as an additional tool at the service of the therapist and can be used by the patient during de-hospitalization or to promote active aging

[Improvement in the quality of life even in old age. Active ageing means where possible, to contribute to the economy and society.]

[Improvement in the quality of life even in old age. Active ageing means helping people stay in charge of their own lives for as long as possible. Each game is identified by a simple graphic and a list of the image, as shown in Figure. Table 3.1 provides a summary of the typology for each game, and here follows a description.

[where possible]:

where possible

(where possible),

where possible

[to contribute to the economy and society]

to contribute to the economy and society

(to contribute to the economy and society)

to contribute to the economy and society

Breath Ball

Note: not used anymore in the current ReMoVES version.

This activity helps the patient to relax and focus on their breathing. It is not an interactive game. The patient is led to breathing with a regular rhythm by following a "breath ball" displayed on the monitor. The Breath Ball exercise makes the subject comfortable and brings back their heartbeat to a basal value before the actual rehabilitation session starts.

Albert, Bisection, and Apple Test (Fig. 3.4a, b, c)

These are a computerized version of the well-known paper-and-pencil test for unilateral spatial neglect. The patient interacts with the test by means of a touchscreen. The system collects data and provides or final scoring automatically.

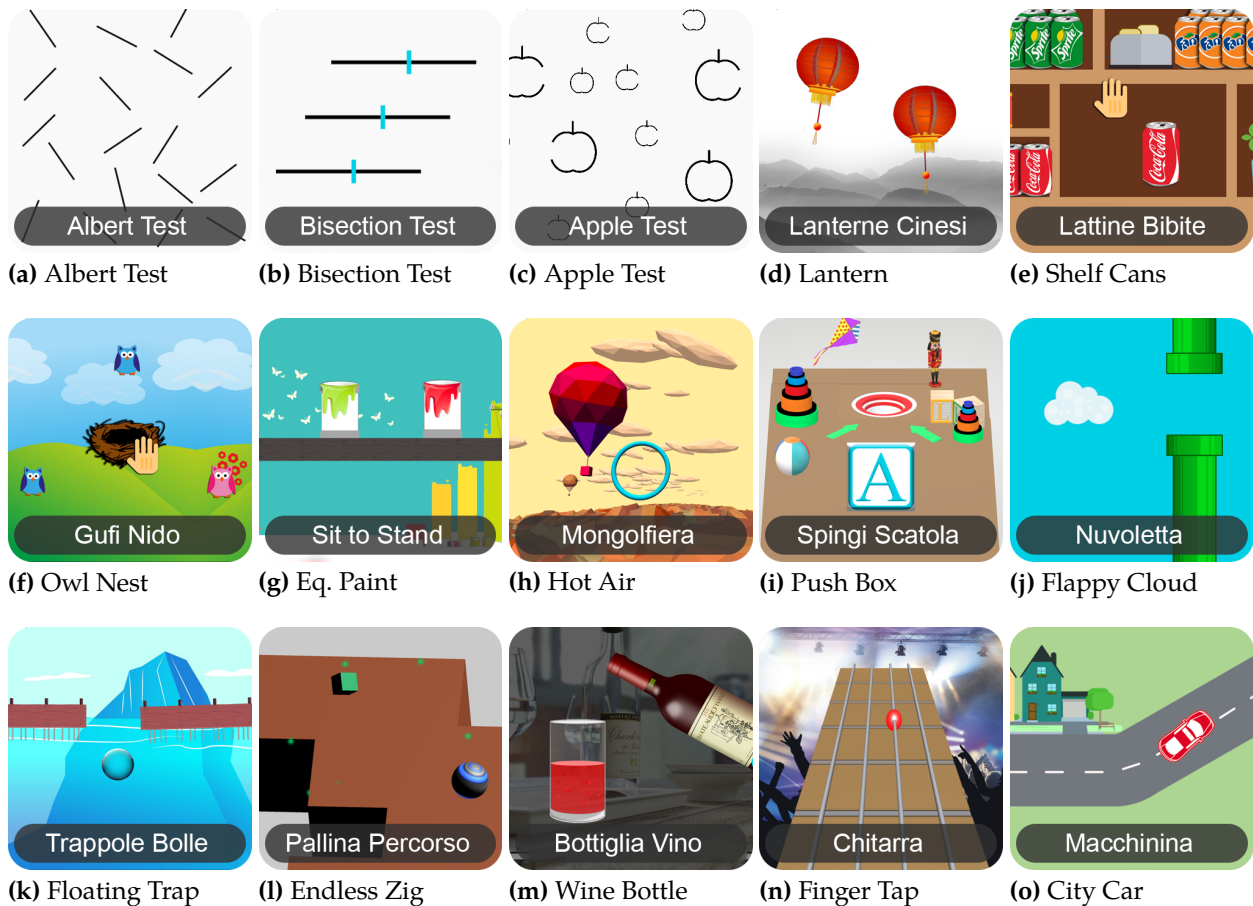


Figure 3.4: Thumbnails of exergames in the current ReMoVES catalog.

Lantern (Fig. 3.4d)

In this exergame, Chinese lanterns appear from the lower side of the screen and rise towards the sky (upper part of the screen). The player must act as quickly as possible and touch them using a touchscreen. This activity is for the assessment of mental alertness and awareness. Moreover, it can have applications for the neglect assessment by comparing the performances relative to the targets shown on the right or left of the screen.

Shelf Cans (Fig. 3.4e)

This exergame introduces the patient to a virtual environment, similar to a kitchen. With the arm movement, the patient grabs one of the colorful drink cans appearing in the middle of the screen and drags it to the corresponding shelf. This game is appealing because it requires the user

to be attentive to drop off the drink can on the correct shelf according to its color.

Owl Nest (Fig. 3.4f)

The patient is encouraged to reach an on-screen target with the arm motion (Reaching Task) in order to achieve a high in-game score. Many colorful owls appear randomly in any position of the screen for a given time-frame: the user should carry them in the nest before they disappear.

Equilibrium Paint (Fig. 3.4g)

This serious game is an interactive version of the Sit to Stand (STS) exercise, typically used in traditional rehabilitation to evaluate patient performance. The user should stand up and sit down repeatedly within a predefined amount of time (30 seconds); their trunk must remain erect: an erroneous lateral shift causes the fall of the cans of paint leaning on an unstable wooden beam.

Hot Air (Fig. 3.4h)

This is an activity to train the patient's body balance. The user can control the direction of a hot-air balloon, floating in the sky with the balance shift: in-game scores are collected when it is led towards the bonus targets.

Push Box (Fig. 3.4i)

PushBox is an exergames of assessment of the balance where the patient must stretch forward with his arms parallel to the ground. It takes inspiration from a phase of the Berg Balance test. The purpose of this exercise is to push a box into a hole a few meters in front of the box.

Flappy Cloud (Fig. 3.4j)

This is a functional exercise for the lower limb. The leg Abduction–Adduction movement reflects the position of a cloud object in the game screen: the patient should make

it move forward without hitting some obstacles.

Floating Trap (Fig. 3.4k)

In this serious game, the patient is led to open their hand and make a fist alternatively. This exercise requires a good level of concentration: in fact, the user moves a floating raft on the left or on the right according to the finger Flexion–Extension in order to avoid some objects in the scene.

Endless Zig (Fig. 3.4l)

In this activity, the patient drives a marble along a zigzag path appearing on the screen. Going out of the boundaries causes score loss; similarly, some bonus gems appear on the path. The patient controls the marble movement with Radial–Ulnar deviation.

Wine Bottle (Fig. 3.4m)

This exercise mimics a real-world scenario: pouring liquids from a bottle. With the Pronation–Supination movement of the hand, the patient should control the rotation of a bottle of wine appearing on the screen. They must fill a glass over and over again to collect as many points as possible.

City Car (Fig. 3.4o)

In this game, the patient drives a car along a randomly-generated road. The user should steer in the presence of curves and crossroads with the movement of Flexion–Extension of the wrist. Penalties are introduced when the user goes off-track.

Breath Ball

To make the subject comfortable and to return their heartbeat to a basal value before the rehabilitation session, the patient is led to breathing with a regular rhythm by following a

Table 3.1: Serious games list including the purpose of the activity, the employed devices, and the indicators that describe the patient performance during the exercise.

Exegame	Activity Purpose	Device
Breathing Ball	Relaxation	Microsoft Band 2
Albert Test	Cognitive	Touchscreen
Bisection Test	Cognitive	Touchscreen
Apple Test	Cognitive	Touchscreen
Lantern	Cognitive	Touchscreen
Shelf Cans	Upper limb	Microsoft Kinect
Owl Nest	Upper limb	Microsoft Kinect
Equilibrium Paint	Sit to Stand	Microsoft Kinect
Hot Air	Balance control	Microsoft Kinect
Push Box	Balance control	Microsoft Kinect
Flappy Cloud	Lower limb	Microsoft Kinect
Floating Trap	Hand, fingers	Leap Motion
Endless Zig	Hand	Leap Motion
Wine Bottle	Hand	Leap Motion
Finger Tap	Fingers	Leap Motion
City Car	Hand	Leap Motion

"breath ball" displayed on the monitor. The ball changes its size, simulating inspiration, and expiration (Figure 3.5): when it grows, the patient should inhale, then exhale when it shrinks. When a patient has had difficulty following the rhythm of the ball, he is invited to relax and not strain.

During the execution of this exercise, the *Heart rate (HR)* signal is acquired. The trend analysis is performed, and the *Angular coefficient* β_{HR} of the straight line that best approximates the heartbeat is computed, to understand the general pattern of the signal. The patient can be considered ready for the execution of physical rehabilitation if β_{HR} is equal to or less than zero. A positive coefficient means a state of fatigue and excitement, not suitable for the aim of the rehabilitation process.

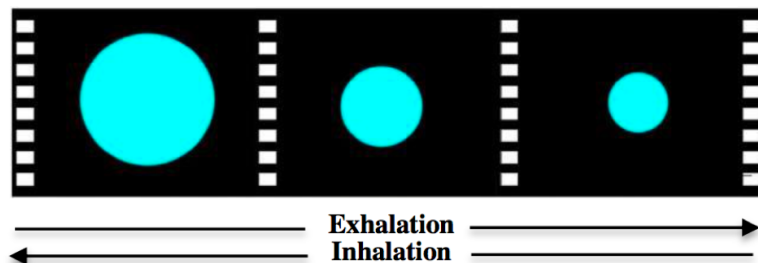


Figure 3.5: Relaxation exercise: the patient inhales as the animation grows, then exhales as it shrinks.

Albert Test

This activity is the digital version of the paper-and-pencil test that is commonly applied in mapping visuo-spatial neglect in clinical practice (2.6). In this test, patients must cross out forty 2.5 cm lines that are placed in pseudo-random orientations on a piece of paper, using a pencil. The actual disposition of these lines is standardized, allowing for a systematic analysis of subjects' performance on the left, the right, and in the middle of the page. Scoring is based on the number and location of lines left uncrossed [90]. In the digital version, the patient interacts with a touchscreen (Fig. 3.6a). Invalid and accidental touches are automatically ignored by the system. The paper-based and the digital test differ in these aspects:

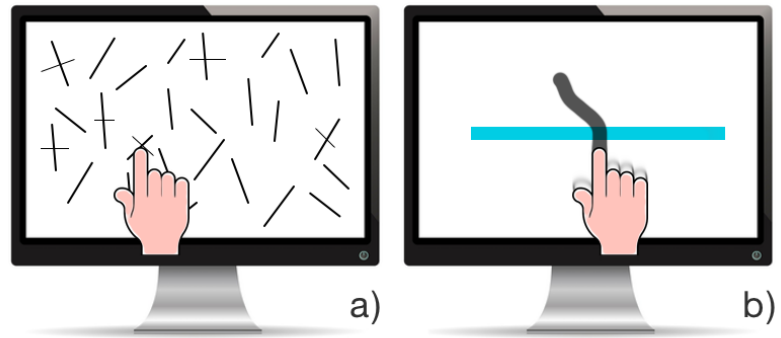
- ▶ patient must be capable of holding a pencil (traditional test) – patient must be able to use a touch screen (digital test);
- ▶ the digital version can provide more granular information on the speed execution and the cross out order.

Bisection Test

This activity is the digital version of paper-and-pencil test for visuo-spatial neglect mapping (2.6). To complete the test, one must place a mark with a pencil through the center of a series of horizontal lines. The test is scored by measuring the deviation of the bisection from the middle of the line [91]. In the digital version, the patient interacts with a touchscreen (Fig. 3.6b). The paper-based and the digital test differ in these aspects:

- ▶ patient must be capable of holding a pencil (traditional test) – patient must be able to use a touch screen (digital test);
- ▶ the digital version allows customization of the color, width, height, position, and rotation of the line in order to provide multiple variants of the standard test and in-depth analysis;
- ▶ the digital version displays a new line whenever the patient manages to cross out the line, continuously up to two minutes. This allows repeating the measurements more times than the traditional test that is based on just three lines.

Figure 3.6: a) Digital version of Albert's test included in ReMoVES platform b) Digital version of Line Bisection test included in ReMoVES platform



Apple Test

[76]: Mancuso et al. (2015), 'Italian standardization of the apples cancellation test'

This activity is the digital version of the Italian standardization [76] of the Apples Cancellation Test: it is a new instrument useful to evaluate both egocentric and allocentric forms of neglect (2.6).

Apple test is a cancellation task in which outline drawings of 150 apples are shown pseudo-randomly scattered over the touchscreen (Fig. 3.7). All of the apples are presented in an upright position. One-third of the apples are full (targets), and two-thirds are open on either the left or the right side (distracting elements). In order to balance the probability that omissions will show left versus right or upper versus lower space neglect, the screen is virtually divided into a grid with two rows and five columns to ensure an equal distribution of the apples across the page. Each cell of the grid contains 15 apples: three large ones (one with no opening, one with an opening on the left and one with an opening on the right) and 12 small apples (four without openings, four with openings on the left and four with openings on the right). The large apples are 50% bigger than the small fruits. Each participant was asked to touch on the screen all the full apples and to ignore all the ones with holes. The ReMoVES platform will perform all the required data analysis to provide a scoring report to the therapist. Additional information than the paper-and-pencil version is provided to offer a complete diagnosis.

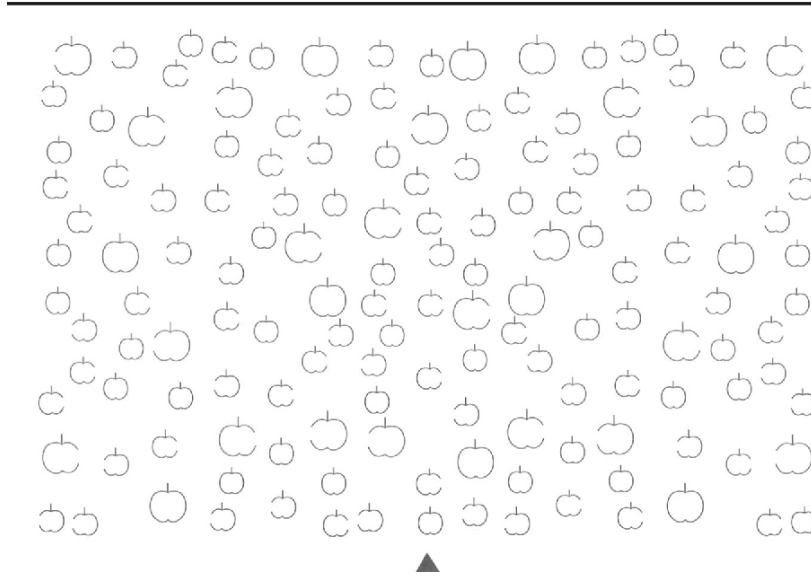
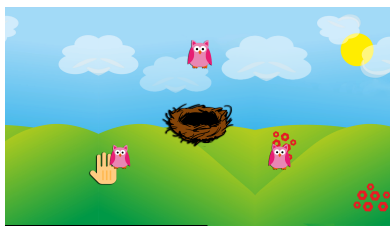


Figure 3.7: Digital version of Apple Cancellation test included in ReMoVES platform

Owl Nest and Shelf Cans

In both Owl Nest and Shelf Cans exergames, the patient is encouraged to reach the consecutive on-screen targets with the arm motion (reaching task) in order to get rewarded with a high in-game score. These games aim at improving coordination, hand-eye coordination, and spatial awareness. An initial calibration phase adapts the game to the user, which can complete the proposed tasks even with reduced mobility. The games are designed to generate a motivating environment to promote physical activity and rehabilitation without causing discouragement.



(a) Owl Nest



(b) Shelf Cans

Figure 3.8: Owl Nest and Shelf Cans: screenshots captured during activity designed for upper limb rehabilitation.

The Owl Nest (Fig. 3.8a) scenario is characterized by stylized owls appearing randomly on the screen: the user has to carry them to the nest placed in the middle. The game auto-adapts the rate of generation of new targets based on the patient's speed, and at the same time, limits to three the maximum number of owls present on the screen if the patient fails to dispose of the queue quickly enough. The Owl Nest is

self-explanatory and suitable for patients with cognitive disabilities.

The Shelf Cans (Fig. 3.8b) promotes upper limb rehabilitation through task-oriented training: the patient practices real-life activities such as storing items on a wall unit. In detail, the game involves moving a colored can of soda towards the corresponding shelf: the up-right, up-left, and bottom-left corners are respectively for orange, green, and red tin cans. Compared to Owl Nest exergame, Shelf Cans contributes to improving the attentive capacities of patients, who must respect the rule of matching the color between the can of soda and the shelf correctly. The penalty in case of error consists of the reduction of the score along with a disappointing sound.

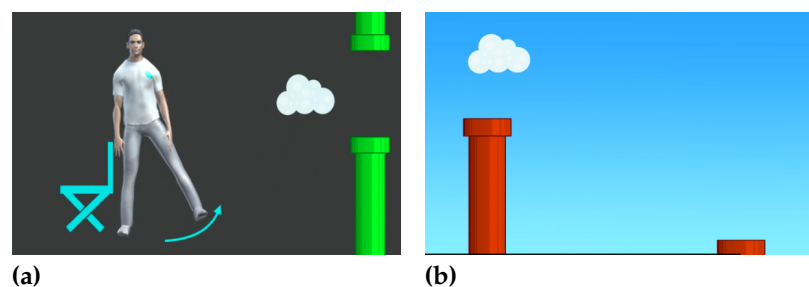
Flexion–extension and abduction–adduction are the main movements at the shoulder joint (glenohumeral joint) tracked during the execution of these functional exercises.

Flappy Cloud

In this game, the player uses the movement of a leg to perform the activity. The patient, possibly assisted by a therapist or caregiver, must prepare the environment:

- ▶ in an upright position;
- ▶ place a chair (facing the backrest) on the opposite side of the limb to be rehabilitated and put the hand on it.

Figure 3.9: Flappy Cloud: screen-shots captured during the calibration and the activity for lower limb rehabilitation.



The exercise consists in restoring the adduction and abduction movements, lifting the leg laterally according to the events in the game. This exergame is designed primarily for patients who have undergone orthopedic surgery, such as a hip or hip fracture. The game consists of controlling the altitude (vertical position on the screen) of a cloud that advances automatically. The elevation of the cloud increases

when the player lifts his leg sideways 3.9. Along the way, some obstacles force the player to move and avoid penalty scores. When the cloud collides with obstacles, it stops for a few seconds, and the patient can try again.

Equilibrium Paint

The game Equilibrium Paint (Fig. 3.10) is an assessment tool with visual feedback for the patient. The patient is guided to perform the traditional STS test described in Section 2.4. The scene shows a horizontal wooden beam on which paint cans are placed. The inclination of the beam directly depends on the angle of the patient's shoulders during the STS traced by Microsoft Kinect. When the patient does not stand up symmetrically, the paint cans fall down, causing a score penalty in the game.



Figure 3.10: Equilibrium Paint: screenshots captured during the activity. This exergame is for Sit to Stand assessment.

HotAir

This exergame shows a 3D interface based on the "low poly" artistic design 3.11. A hot-air balloon flies over a hilly landscape and advances automatically. The player can control the lateral displacement of the balloon by performing a load shifting exercise between the lower limbs. In particular, the Microsoft Kinect is used to estimate the player's center of mass by evaluating some angles at significant joints. The aim of the game is to guide the balloon towards the blue rings that appear along the way.

The progressive position of the rings is pseudo-random and tuned so that there is a continuous load shift. The patient who

Figure 3.11: Hot Air: screenshots captured during the activity. This exergame is for load shift between lower limbs.

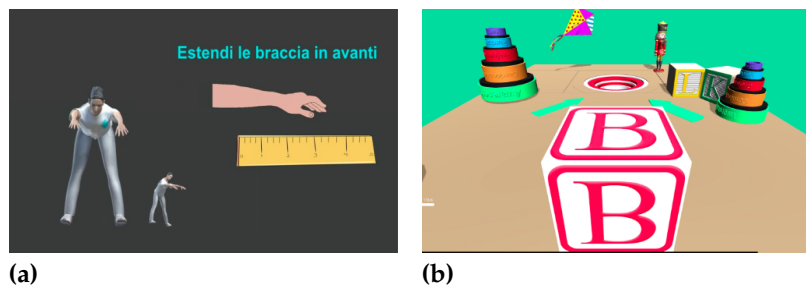


wants to maximize the score must alternate a considerable force on the right limb, followed by a load on the left one. The game is inspired by video games like Nintendo Wii Sport that imitate sports activities such as "skiing". These commercial games are sometimes already used at rehabilitation centers but are not adequate for unhealthy individuals. Older patients with cognitive deficits or limited motor skills fail to understand or adequately play the game. Hot Air instead is simple and suitable for a large number of patients.

Push Box

3: The Berg balance scale is used to objectively determine a patient's ability (or inability) to safely balance during a series of predetermined tasks. It is a 14 item list with each item consisting of a five-point ordinal scale

Figure 3.12: Push Box: screenshots captured during the calibration and the activity for balance control assessment.



In the Berg test, the therapist measures the ROM: he takes care of measuring the distance between the tip of the feet and the projection on the floor of the tips of the hand. The exergames, by means of Microsoft Kinect, computes this

calculation in real-time and performs other checks on the patient's position.

1. The arms must be parallel to the ground: the angle among straight line shoulder-wrist and the horizontal plane must be between -30 and +30 degrees (for each arm).
2. The arms must not be folded: the angle shoulder-elbow-wrist must be between 140 and 210 degrees (for each arm).
3. The arms must be parallel to each other: the angle right wrist-chest-left wrist must be less than 40 degrees (for each arm).

Regarding the phases of the game, there are 4 phases contained in a switch-case statement:

- **Phase 0:** Waiting for the validity position of the player; when it happens the switch goes in case 1;
- **Phase 1:** If the validity position is true, waiting for the achievement of the 85% of the maximum ROM of the player; if it happens, the switch goes in case 2. If the validity position becomes invalid, the switch comes back in case 0.
- **Phase 2:** The animation of the box starts; waiting for the falling of the box into the hole, then the switch goes in case 3.
- **Phase 3:** Waiting for the player's hands come back ROM: $\leq 70\%$ of the maximum ROM; a new box is instantiated in the start position, and the actual box is destroyed. The new box restarts at phase 0.

The phases block diagram is in Figure 3.13.

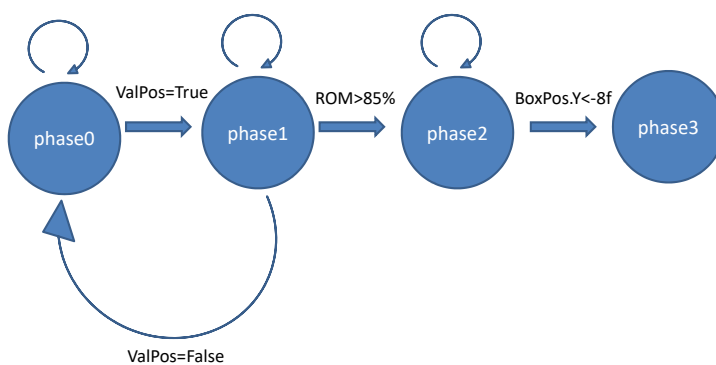
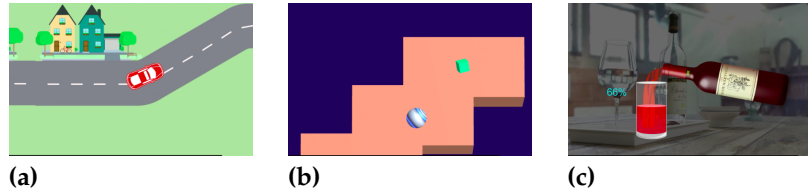


Figure 3.13: PushBox exergame phases.

CityCar, Endless Zig and Wine Bottle

These three exergames promote the rehabilitation of the hand and wrist, by means of the Leap Motion controller. Each game targets a specific hand movement: pitch, yaw, and roll 3.14.

Figure 3.14: CityCar, Endless Zig and Wine Bottle: screenshots captured during the activities for hand rehabilitation.



In the first exergame, the patient performs the Flexion-Extension of the wrist to drive a red car along a path. The scene is in 2D with a view from above. The car speed increases progressively and reverts to the initial condition as soon as the player makes a mistake, coming out of the carriageway.

In the second exergame, the patient performs a Radio-Ulnar deviation to guide a ball along a path. The scene is a 3D environment, where the way to follow is generated dynamically and randomly as you advance. The speed of the ball progressively increases but returns to the original rate as soon as the player makes a mistake, making the ball fall off the course. The game is made more complicated by the presence of bonus gems along the way, which offer extra in-game points.

In the last exergame, the patient performs a (partial) Pronation-Supination of the hand. The rotation of the patient's hand controls the angle of the inclination of a bottle of wine. Once the proper angle is reached, the wine is poured into a glass. When this is full, the patient will earn points and can repeat the procedure.

Floating Trap

This exergame uses the Leap Motion as a finger tracking device. The patient must alternate an extension and closure movement of the fingers to check the position of two rafts floating on the water. Meanwhile, from the depths of the water, a bubble of air rises towards the surface. The bubbles must not hit the rafts, or they will explode, causing in-game score loss 3.15. The game is stimulating at a cognitive level,

due to the coordination of the movement with the game scene.

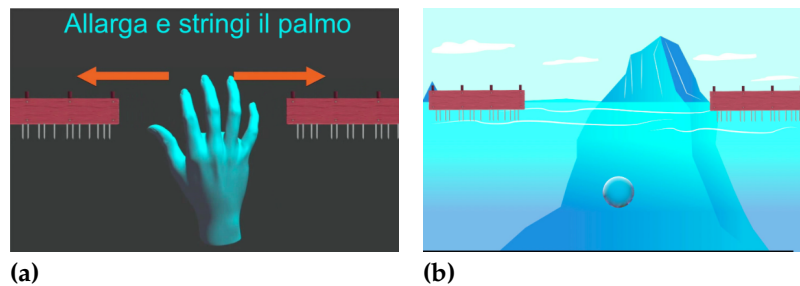


Figure 3.15: Floating Trap: screenshots captured during the calibration and the activity for hand rehabilitation.

3.3 Architecture

The proposed solution follows the client-server architecture. The clients consist of the constellation of units used by the patients at home or the care centers. The software running on the server can manage content-independent data flow to be compliant with the software reuse logic. Indeed, the platform currently receives motion activity data from exergames, but it is meant to receive a wide spectrum of data types flawlessly. The server software consists of a traditional LAMP stack⁴ and provides data storage solutions, data processing methods, and a web-application for clinicians to consult information through dedicated graphic interfaces and assign rehabilitation therapies to patients.

Furthermore, the software running on the server offers an interface to allow communication with any device category or the operating system running on the client units. For example, the client units could range from a smartphone running Android or Apple iOS, to a Android TV set-top box, from a simple IoT device to a personal computer running full Microsoft Windows. Any third party developer of client units can opt for their preferred solution to transmit data to the ReMoVES platform thanks to a series of Application Programming Interface (APIs). They are REpresentational State Transfer (REST) compliant, run over HTTPS for improved security, and rely on the widely adopted JavaScript Object Notation (JSON) for data format.

4: LAMP (Linux, Apache, MySQL, PHP) is an archetypal model of web service stacks, named as an acronym of the names of its original four open-source components: the Linux operating system, the Apache HTTP Server, the MySQL relational database management system (RDBMS), and the PHP programming language. [https://en.wikipedia.org/wiki/LAMP_\(software_bundle\)](https://en.wikipedia.org/wiki/LAMP_(software_bundle))

Client side

In the current version of ReMoVES, the software running on the client devices is an application developed with Unity 3D, which includes services for data communication with the server, the user interfaces for the authentication of the player, and the set of exergames. The supported operating system is Microsoft Windows 10 (x86 or x64): currently tested and fully compatible with the May 2019 Update (version 1903). The minimum requirements of the hardware platform on which the system can be installed are:

- ▶ Processor: Sixth Gen Intel®Core™i3 CPU (Dual Core 2.4 GHz or faster);
- ▶ Memory: 4 GB of RAM;
- ▶ Storage: 20 GB;
- ▶ Video Card: DirectX 11-capable from NVIDIA, AMD or Intel;
- ▶ Other: Dedicated USB3 port.

Recommended Hardware Requirement:

- ▶ Processor: Seventh Gen Intel®Core™i5 CPU (Quad Core 2.4 GHz or faster)
- ▶ Memory: 4 GB of RAM;
- ▶ Storage: 20 GB on Solid-state drive (SSD);
- ▶ Video Card: DirectX 11-capable from NVIDIA, AMD or Intel with at least 1GB of VRAM;
- ▶ Other: Dedicated USB3 port.

The commercial products that have been identified as the best compromise between performance, cost, and compactness are the Ultra-Compact PCs of the Brix™series produced by Gigabyte®([Gigabyte GB-BSi3H-6100](#)) or similar products of other brands.

The internet connection is not mandatory for the user identification phase and to start the exergames locally, but it is necessary –at least occasionally– for data synchronization with the server. Therefore, networking is required for the project workflow, although the architecture allows local data caching. This functionality has been implemented to limit the problems deriving from a connection that is not stable or not always available in some locations. Under normal conditions, the platform requires all clients to be permanently connected to the network.

Launch flow

This section describes the flow required to start the client platform. A flowchart is provided in Figure 3.16.

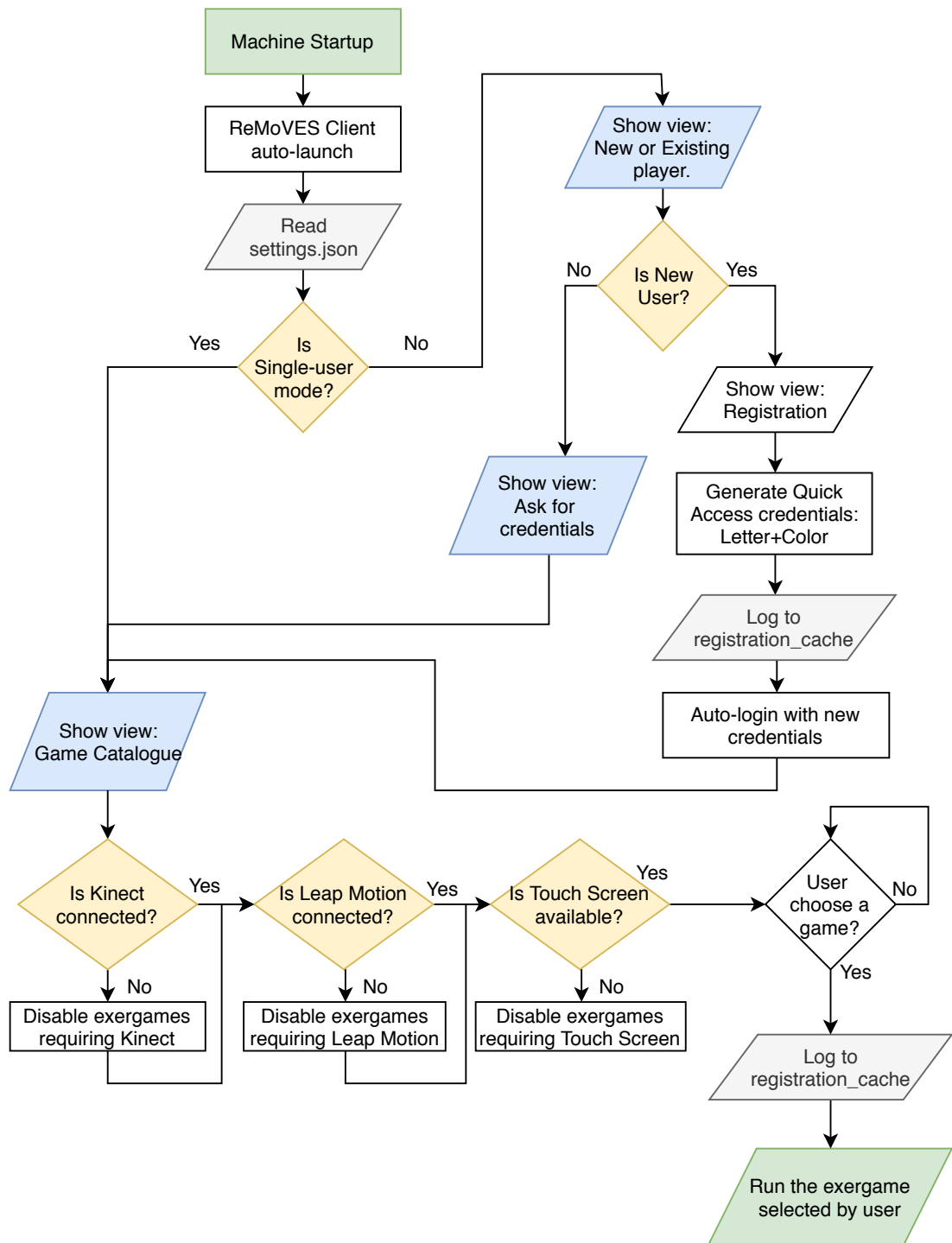


Figure 3.16: ReMoVES Client workflow including phases from startup to the exergame launch.

When the machine is turned on, an automatic boot system automatically launches the ReMoVES software without any user interaction. At the same time, the system takes care of reading the *settings.conf* file, which contains the basic configuration necessary for the authentication phase. Below is shown its content, and the purpose of each key will be progressively clarified:

```

1 {
2   "single_user": "0",
3   "seatKey": "bTRERxDq5XfrxuMh",
4   "user_email": "patient0@mail.com",
5   "user_pass": "secret123",
6   "characterKey": "0",
7   "colorKey": "0"
8 }
```

Authentication occurs in two different modes, specified in the *single_user* key:

- ▶ **single user:** when used by an individual patient at home, the system is delivered pre-configured with the credentials *user_email* and *user_pass* within *settings.conf*, which trigger the auto-login procedure, entirely transparent for the user;
- ▶ **multi-user:** when used in sharing contexts such as at rehabilitation centers. Each patient is identified with "quick access" credentials (details to follow).

In the latter case, the software shows appropriate screens so that the player can:

- ▶ **register** for the first time: supported by the therapist, the patient provides general information such as age and sex, and the system assigns quick access credentials, valid for 60 days. This action is logged in *registration_cache.json* local file and synchronized with the server as soon as the internet is available;
- ▶ **authenticate** with "quick access" credentials already in possession.

The "quick access" credentials are constituted by:

- ▶ a single letter (*characterKey*) from a subset of the alphabet (20 characters);
- ▶ a color (*colorKey*) between blue, purple, green, orange, red (5 colors);

- the *seatKey* key (pre-configured in *settings.conf*), which uniquely represents the device in use.

With this mode, the patient only needs to remember a letter and a color to be able to start the exergames in the ReMoVES platform: the credentials are valid for 60 days and are on the device on which they were generated. Therapists usually donate cards the size of a business card with the letter and color assigned to the patients to help them to remember their credentials (example in Fig. 3.17).

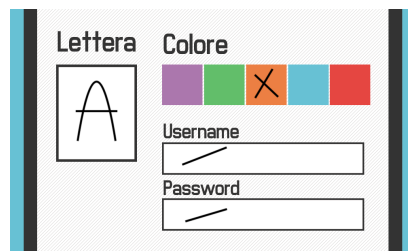
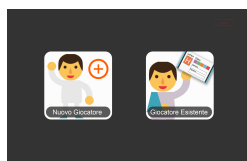
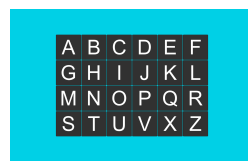


Figure 3.17: "Quick Access" credentials assigned to a patient. Therapists can provide cards with the letter and color assigned to the patients, to help them to remember their credential.

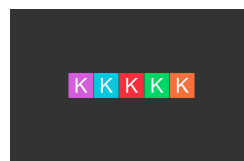
When the login took place 3.18, the ReMoVES software shows the "Game Catalogue" screen or starts the Plan of Care established by the therapist (if provided).



(a) Owl Nest



(b) Owl Nest



(c) Owl Nest

Figure 3.18: Login phase in ReMoVES platform, based on multi-user "Quick Access" mode.

The "Game Catalog" screen is a grid where each exergame is represented by a name and a representative image. The system automatically takes care of disabling the games not usable with the current client configuration: in detail, the exergames that require the Microsoft Kinect, the Leap Motion, or a Touchscreen screen are grayed out when the respective peripherals are not connected. This functionality makes ReMoVES modular and customizable according to the needs of the rehabilitation center.

When the patient chooses the game to be started, the action is recorded in the local *session_cache* file and synchronized with the server as soon as the internet is available, together with the data that will be collected during the same exergames.

When the patient chooses the game to be started, the action and the timestamp are recorded in the local file *session_cache.json* and synchronized with the server as soon as the

internet is available, together with the data that will be collected during the same exergames.

Exergames

The exergames are developed with Unity 3D and share some common components. To facilitate the development, "Prefab" components have been created, foreseen by Unity 3D itself, according to reuse principles. In particular, the prefab "LogData" allows easy integration of exergames with the client/server architecture of ReMoVES. After creating a new exergame, it is sufficient to insert this preset in the scene to have access to useful features even when the developer does not have competence regarding communication through RESTful APIs. The "LogData" preset has been specifically developed for ReMoVES clients to manage without any intervention by the programmer:

- ▶ the countdown of the remaining time (showing a thin black bar on the lower edge of the screen);
- ▶ display of the final score obtained by the patient;
- ▶ display of the final score obtained by the patient;
- ▶ return to the exergame selection screen after the "game over";
- ▶ the abort of the current session in case of error;
- ▶ the log of the complete movement data (full joints set) coming from the Microsoft Kinect or from the Leap Motion (if connected) to the frequency of 10 Hz;
- ▶ the log of the specific data of the game, for example, a counter of the wrong targets;

The simplicity of the LogData prefab is demonstrated below with an example through a piece of code extracted from the CityCar game. In the Update() routine –which is executed at each frame along with all the necessary operations– the LogData preset is used for logging the car's instantaneous speed.

```

1 void Update()
2 {
3     ...
4     LogData.updateActivityData("speed", speed);
5 }
```

With this command, together with the hand movement data provided by the Leap Motion, it is possible to keep track of any additional data and automatically find it in the data synchronized with the server.

The client generates a log in JSON format, which collects temporal events as an array. In each element of the array, there are key-value pairs that provide the data.

```

1 [
2   {
3     "time": "63693953720654",
4     "score": "10",
5     "speed": "2.00402",
6     "wrongPath": "0",
7     "evaluation": "0",
8     "leapmotion": [...]
9   },
10  {
11    "time": "63693953720755",
12    "score": "10",
13    "speed": "2.00704",
14    "wrongPath": "0",
15    "evaluation": "0",
16    "leapmotion": [...]
17  }

```

Server side

The architecture of the ReMoVES platform assigns most of the data management tasks to the server since the client side has a mere data collection function. This section explains the functions performed by the server, which can be summarized as follows:

- ▶ Expose RESTful APIs for data sync;
- ▶ Store data in MySQL database;
- ▶ Process data.

Server APIs

Currently updated to version v3, following an internal simplification, the ReMoVES server exposes only three types

5: Let's Encrypt is a non-profit certificate authority run by Internet Security Research Group (ISRG) that provides X.509 certificates for Transport Layer Security (TLS) encryption at no charge <https://letsencrypt.org/about/>

of APIs for the management of client/server data synchronization. Data communication is in a secure mode based on Hypertext Transfer Protocol Secure (HTTPS). In HTTPS, the communication protocol is encrypted using Transport Layer Security (TLS). Certificates are issued by the Let's Encrypt authority ⁵.

{endpoint}/v3/setRegistration

Method: POST

Synchronization with the server of new patient registrations occurred on the client side.

Reading the content of registration_cache.json, the client sends a list of all the patients who have recently registered on the system. In case the client has not had access to the internet for a long time, the server expects multiple entries.

{endpoint}/v3/setSession

Method: POST

The client provides the server with the list of exergames sessions started on the client.

Reading the contents of session_cache.json, the client sends a complete log of the started game sessions, with precise details on the starting time, the player authenticated, and the unique identifier of the session.

{endpoint}/v3/store

Method: POST

The client sends the full log data of a single exergame session.

This API is called by the client in the background and allows the data collected during the game session to be sent to the server. The size of each individual log is usually in the order of 1MB (up to 4MB). If the client is without internet, a queue is set up and the log files are sent one by one as soon as the connection is restored.

Database

This section describes the MySQL relational database used by ReMoVES. Figure 3.19 provides a graphical representation of the schema and the relationships between the tables.

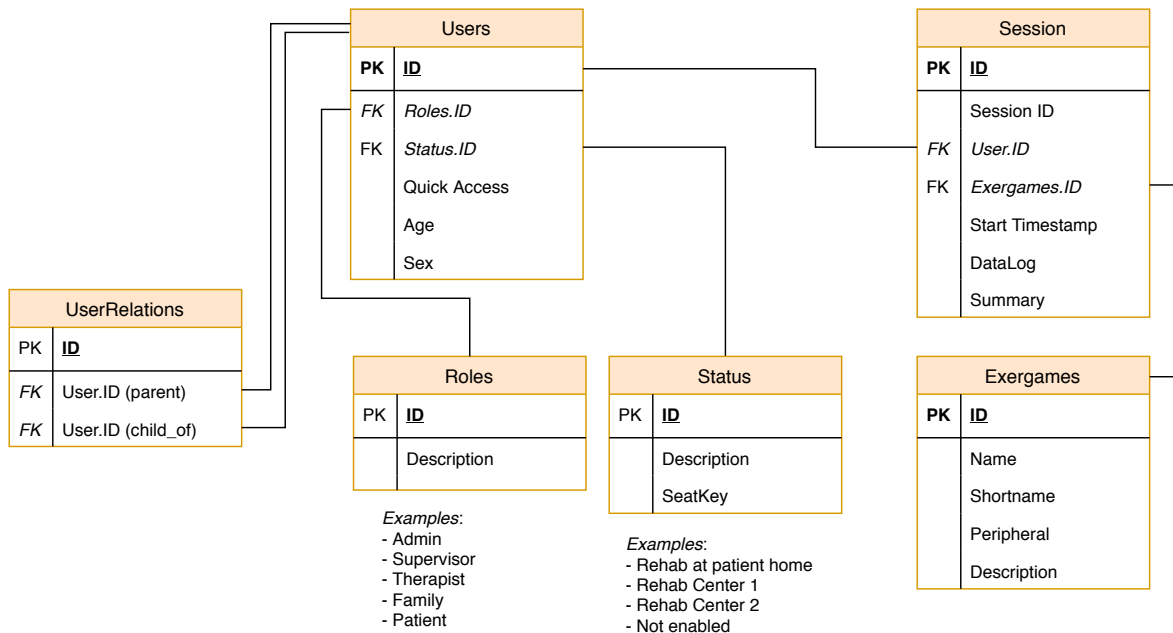


Figure 3.19: MySQL relational database structure of ReMoVES platform.

The table *Users* is populated with the data of both patients and other users who can access the platform: administrators, supervisor (designed for heads of rehabilitation facilities), therapist, family (relatives of a patient). Of great importance is the *UserRelations* table, which allows users to be assigned with one-to-many relationships: in particular, it is used to guarantee the hierarchy between the Roles (for example assigning patients to a therapist). The Patient type requires additional information such as age, sex, diagnosis, and the location where ReMoVES is used (autonomously at home or at the specified rehabilitation center).

The *Sessions* table contains the log of the sessions conducted by the players. It uses the identifier of the user and the one that describes the type of exergames as foreign keys. Thanks to this classic structure, search filters on these two parameters can be applied efficiently. This table stores the exergames log data sent by the client in "DataLog" file using the JSON Data Type included recently by MySQL in version 5.7.8+.

According to official MySQL documentation, the JSON data type defined by RFC 7159 provides these advantages over storing JSON-format strings in a string column:

- ▶ Automatic validation of JSON documents stored in JSON columns. Invalid documents produce an error.
- ▶ Optimized storage format. JSON documents stored in JSON columns are converted to an internal format that permits quick read access to document elements.

Although it is a feature introduced in MySQL only recently, its use has been deemed efficient compared to using other data storage systems, such as NoSQL solutions or direct disk storage.

Finally, the *Session* table provides the "Summary" field. The data processing processes running in the background on the server summarizes the raw data contained in "DataLog" and stores the results in the Summary field, for faster access to synthesized data.

Data Processing

The raw data records sent by the clients contain complete information about the events during the exergame sessions. When Microsoft Kinect and Leap Motion devices are employed, the entire set of 3D data is recorded for each articulation (Fig. 3.1 and Fig. 3.2).

In the early stages of development of ReMoVES it was decided to log the tracking of joints strictly legal to the exergame in question and only at the frequency of 2 Hz: for instance, in the games for the upper limbs, the lower extremities were ignored. However, with the support of the clinical staff, it was considered appropriate to keep track of all the information made available by the sensors and to increase the frequency to 10 Hz. The complete tracking of the body (Microsoft Kinect) or the entire hand (Leap Motion) at 10 Hz provides more comprehensive movement data and to know the patient's status. For example, in the exergames for the upper limbs, it can also be crucial to carry out measurements on the balance of the trunk or the positioning of the lower extremities, to highlight any erroneous or compensatory movements. As a direct consequence, however, the raw data logs have grown considerably in size and can contain data that is not very useful for the therapist. The data processing aimed

at summarization is, therefore, necessary and performed by routines in the background on the server. Recalling that ReMoVES is meant to be an additional tool to support the therapist, algorithms are highly specialized for each exergame intending to provide objective measurements and data based on patient performance.

As shown in Figure 3.20, the raw data received from the clients are stored in the *Session* table using the *DataLog* field. A background routine executes the specific algorithms for exergame and puts the results (synthesized data) in the *Summary* field of the *Session* table. In this way, both the original data (heavier but untouched) and the summarized (accessible more quickly) always remain available, and the latter can be overwritten in case of improvements in the analysis algorithms. These are currently developed in PHP, while it is possible to introduce processing modules in any language able to connect to a MySQL database. A reliable choice could be Python, which, thanks to the numerous libraries dedicated to data processing, is an excellent tool for scientific uses.

The methods of summarizing the data for visualization and the results are presented in Chapter 4 and 5.

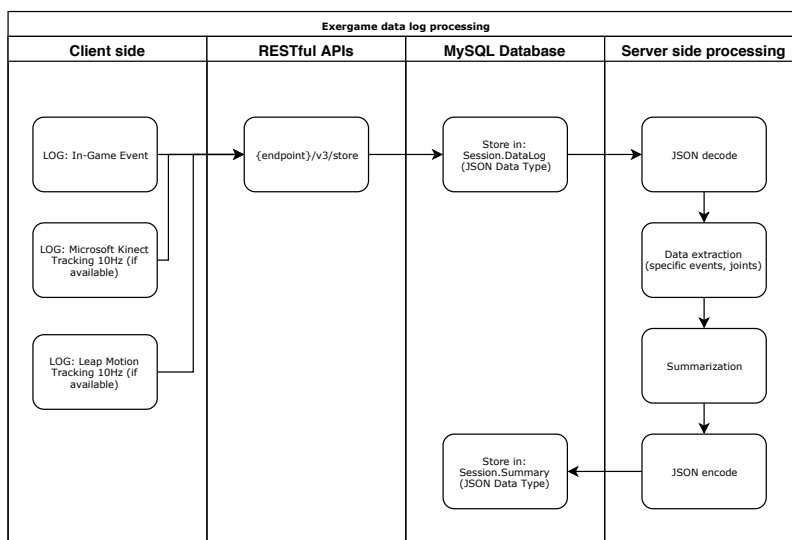


Figure 3.20: Data flow from exergames: the raw data is sent from the client to the server with RESTful APIs and stored in the SQL database. Subsequently, a background routine takes care of processing and synthesizing the data, saving them in a dedicated field of the table dedicated to the sessions for immediate access.

Web Interface

The server used by ReMoVES also performs Web Server functions. The management is entrusted to the open-source panel VestaCP⁶ and is based on Apache / 2.4 combined

6: VestaCP is a free, open-source, and powerful website control panel that comes with website, email, database, and DNS functionalities. <https://vestacp.com>

with nginx as Reverse Proxy. The web interface allows user-friendly interaction with the features offered by ReMoVES. The back-end is written in PHP, and the front-end uses the Bootstrap 4 and jQuery framework. Thanks to Bootstrap 4, the portal is "responsive", since its layout dynamically adapts to the size and type of device: this allows connection even from mobile devices, ensuring the proper level of accessibility. For example, the therapist can check the progress of his patient also if he does not have a computer available, using his smartphone with any operating system.

The panel offers different tools depending on the hierarchical level of the logged-in user. When used by users with elevated privileges, such as administrators, all the data available on the platform are visible: it is possible to download raw data in JSON format for processing with external software or use search filters. These tools are useful for academic reasons and have therefore been developed specifically to conduct and speed up the present study. A user with lower privileges, on the other hand, will have access to restricted information: a therapist will be able to inspect the performance of his patients only, access the summarized data, and view summary graphs.

Examples of data visualization are presented in Section 5.3.

The development of the ReMoVES platform took three years and followed two branches in parallel:

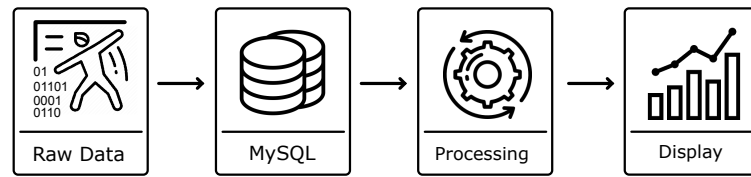
- ▶ delivery of a usable product by end-users (patients and clinical staff) in the short term, to start collecting data as soon as possible;
- ▶ implementation of research tools in order to introduce innovation in the system, to differentiate itself from similar existing solutions.

Below are three methods for data analysis. The first is the most immediate and linked to the first branch of ReMoVES development: the raw data acquired are selected and visualized through graphs so that the therapist can quickly visualize the patient's performance. The second method introduces classification techniques to automate the evaluation of game sessions after extracting significant features. Finally, the last approach paves the way for future developments by applying a neural network-based machine learning system.

4.1 Method 1: Data Analysis

This method was developed through close collaboration with professionals with complementary skills. During the three years of the study, every new step was subjected to the judgment of the clinical staff, which evaluated whether the output graphs and extracts proposed indicators could be easily understood and aid in the evaluation of the rehabilitation progress of patients. It was, therefore, not necessary to make a usage/satisfaction test with a population of therapists, because the method has been constructed precisely with their support. Through data processing (Fig. 4.1), the most important features are extracted and represented with graphs and figures. Thus, these data are better understandable and immediately available to therapists and medical staff, helping them to achieve an accurate interpretation.

Figure 4.1: Data management flow in ReMoVES. The raw data is stored in a MySQL database and processed to provide the therapist with summarized data relating to the patient's performance. The data is mainly shown by means of graphs and indicators.



The proposed method was structured according to the following basic principles:

- ▶ Data aggregation, where multiple data sources may be combined (in-game events with motion data from Microsoft Kinect or Leap Motion);
- ▶ Data selection, where data relevant to the analysis task are retrieved from the database;
- ▶ Data transformation, where data are transformed and consolidated into forms appropriate for processing;
- ▶ Data processing, the essential process where intelligent methods are applied to extract information of interest;
- ▶ Graphical presentation, where visualization and knowledge representation techniques are used to present mined information to the therapist.

The first three phases are different forms of data manipulation that prepare data for processing. The last phase uses the results obtained from the processing stage to propose different views that make information direct, clear, and easy to read. By processing the data and extracting the patient performance indicators, it is possible to provide the therapist with aggregated information of a single session, an entire therapy, an individual patient, or multiple patients; the therapist could then compare these parameters. By applying this method, therapists can easily access daily or periodical patient information without having to process the data or read lengthy reports. In addition, this approach does not exclude physicians from viewing individual patient data of interest.

For the manipulation of the raw data coming from exergames, a software library has been developed that offers some functions that can be used independently of the analyzed game. Some of these tools are commonly provided by libraries for scientific computing and technical computing, typical of languages such as Python or MATLAB. The PHP

language[PHP is a language originally designed for web development.

[PHP is a language originally designed for web development. PHP code is usually processed by an interpreter implemented in C. PHP is a language originally designed for web development. PHP code is usually processed by an interpreter implemented in C. (PHP is a language originally designed for web development. PHP code is usually processed by an interpreter implemented in C. PHP is a language originally designed for web development. PHP code is usually processed by an interpreter implemented in C.

was used for the ReMoVES backend. This choice is motivated by the previous experience of the author in the development of web applications with this technology, which stands among the most common languages used for the development of dynamic websites. PHP offers limited out of the box tools for scientific computing. For this reason, the following methods have been implemented from scratch.

medianFilter (array \$values , int \$order)

medianFilter returns the resulting array from the application of an one-dimensional median filter of \$order to \$values.

removeOutliers (array \$values , int \$magnitude)

removeOutliers returns the resulting array from the removal of all numbers of \$values that fall outside of the mean +/- the standard deviation times the \$magnitude.

distance3D (array \$pointA , array \$pointB)

Given 2 sets of coordinates in the 3 dimensional Cartesian coordinate system, *distance3D* returns the shortest path distance between them.

angle3D (array \$pointA , array \$pointB, array \$pointC)

Given 3 sets of coordinates in the 3 dimensional Cartesian coordinate system, *angle3D* returns the angle between the vectors \$pointB-\$pointA and \$pointB-\$pointC.

filterSuccessiveDuplicates (array \$values)

filterSuccessiveDuplicates return the resulting array after removing the successive duplicates occurrences of \$values. If \$values keeps track of a temporal sequence, the returning array will contains only the changes of state.

linearRegression (array \$x , array \$y)

linearRegression attempts to model the relationship between two variables by fitting a linear equation to observed data.

extractType (int \$sessionid , string \$key)

extractType is a specific function for the ReMoVES platform. Simply indicating the session ID and the desired data type, returns the array of temporal data acquired during the exergame session, decoding the raw JSON file directly from MySQL database. When used to extract motion data from Microsoft Kinect or Leap Motion it automatically detects the "kinect" and "leapmotion" sub-keywords and the specified spatial coordinate. For instance, "kinectHandLeftX" returns: Microsoft Kinect → Hand Left → X coordinate.

These tools speed up the most common tasks needed when processing raw data from exergames. Considering, for example, an activity that uses Microsoft Kinect, it is frequent to calculate the Range of Motion (ROM) at a specific articulation (e.g., the shoulder). It is not intuitive for the therapist to read the spatial coordinates of the joints tracked by Microsoft Kinect. Still, it is preferable to directly visualize the width of the shoulder angle over time, highlighting the maximum and minimum. Also, considering an activity for the cognitive rehabilitation of patients with neglect, the therapist needs automatic counting systems that show summarized numerical values related to the interaction in the different parts of the screen, to evaluate the attention and awareness difference in the two sides of the visual field.

Section 5.3 examines in depth the results of raw data processing to provide the therapist with the data required for assessing the patient's performance. Different graphical representation tools are used depending on the type of game to highlight the most significant indicators.

4.2 Method 2: Classification via SVM

To introduce innovation and provide an ultimate support tool for the clinical staff, ReMoVES includes machine learning techniques for assessing patient performance. In particular,

the main objective of the platform is to identify when the patient achieves low performance in exercises automatically. This possibility is combined with the general idea of the system designed for a home rehabilitation perspective where the player performs the activities independently. Hypothetically, only if the patient does not play correctly, the therapist would be alerted. This method introduces the Support Vector Machine (SVM) technique, which is a robust and reliable classification and regression system. In particular, in the current development phase, ReMoVES integrates a classification system with only two classes: "Good" or "Other". In the first case, the patient carried out the session correctly; in the latter something was not performed successfully, and therefore, the therapist should investigate the reasons more deeply (for example, using information from Method 1). As an additional feature, the classification method included in ReMoVES can follow two different approaches:

- ▶ Patient-specific model: the patient, in this case, performs a considerable number of sessions at the rehabilitation center under the supervision of a therapist. In such a way, a specific model is created based only on the sessions carried out by patient himself.
- ▶ General model: it uses all sessions acquired over time by all patients to create a general model that can be used to all people and can guarantee good but not specific performances. In this case, sessions at the rehabilitation center under the supervision of a therapist are not required.

At home, the patient can play with exergames, and the evaluation is done automatically according to the employed model. After, the results can be sent directly to the therapist who, in the case of the bad performance of exercises, can call the patient for a consultation.

Introduction to SVM

The Support Vector Machine (SVM) is a supervised learning technique applicable to both classification and regression. The basic algorithm was designed by Vladimir N. Vapnik

The credits for section Introduction to SVM goes to:
Mauro Parodi — Classificazione e regressione;
Chris Bishop, Dan Klein, Stuart Russell, Andrew Moore — Linear Classification and Support Vector Machines.

and Alexey Ya. Chervonenkis in 1963 and expanded in 1992 for non-linear classification leveraging on kernel functions.

The supervised classification involves the training of a model based on a series of training examples (or data points), each labeled as belonging to one or the other of two categories. The algorithm assigns new samples to one of the two groups, thus providing a non-probabilistic binary linear classifier. To do this, SVM creates a plan (or a hyperplane, in case the dimensions of the data points are > 2) that separates the two classes; the best choice is to choose a hyperplane that represents the most significant separation, or margin, between them. All of this falls within the resolution of a minimization problem.

Constrained minimization problem and Lagrangian

A constrained minimization problem for a function $f(\mathbf{x})$ can be formalized in the following way:

$$\min_{\mathbf{x}} f(\mathbf{x}) \quad (4.1)$$

with constraints

$$h_j(\mathbf{x}) = 0 \quad (j = 1, \dots, p)$$

$$g_i(\mathbf{x}) \geq 0 \quad (i = 1, \dots, m)$$

The problem 4.1 it is not necessarily convex.

To consider the constraints in 4.1 it can be added to the function a weighed sum of the constraint functions, obtaining the *primal Lagrangian*:

$$L_P(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\nu}) = f(\mathbf{x}) - \sum_{i=1}^m \lambda_i g_i(\mathbf{x}) - \sum_{j=1}^p \nu_j h_j(\mathbf{x})$$

The coefficients λ_i, ν_i are called *Lagrange multiplier*.

The minimum value of L_P over \mathbf{x} is defined *Lagrange dual function* $L_D(\boldsymbol{\lambda}, \boldsymbol{\nu})$:

$$L_D(\boldsymbol{\lambda}, \boldsymbol{\nu}) \doteq \inf_{\mathbf{x}} L_P(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\nu}) \quad (4.2)$$

It can be demonstrated that $L_D(\lambda, \nu)$ is concave, even when the problem 4.1 is *not convex*.

Another property is that L_D yields lower bounds on the optimal value p^* of the problem 4.1. Therefore for each $\lambda > 0$:

$$L_D(\lambda, \nu) \leq p^* \quad (4.3)$$

For each (λ, ν) the function L_D gives a limit that is lower than p^* ; hence it comes

$$\max_{\lambda, \nu} L_D(\lambda, \nu), \quad \lambda \geq 0 \quad (4.4)$$

is always convex.

If it denotes d^* the optimal value of (4.4), the inequality

$$d^* \leq p^* \quad (4.5)$$

holds though the primal problem (4.1) is not convex. This property is called *weak duality* and brings at $(p^* - d^*) \geq 0$. If $p^* = d^*$, we say that *strong duality* holds. It can be had (but it is not sure) if the primal problem is convex.

A solution to this problem is given by the Karush-Kuhn-Tucker (KKT) conditions that ensure strong duality in case of a convex problem. These conditions are:

$$\nabla f(\mathbf{x}^*) - \sum_i \lambda_i^* \nabla g_i(\mathbf{x}^*) - \sum_j \nu_j^* \nabla h_j(\mathbf{x}^*) = 0 \quad (4.6)$$

$$g_i(\mathbf{x}^*) \geq 0 \quad (4.7)$$

$$h_j(\mathbf{x}^*) = 0 \quad (4.8)$$

$$\lambda_i^* \geq 0 \quad (4.9)$$

$$\lambda_i^* g_i(\mathbf{x}^*) = 0 \quad (4.10)$$

The operator ∇ indicates the gradient over \mathbf{x} .

The (4.6) corresponds to $p^* = \min_{\mathbf{x}} L_P(\mathbf{x}, \lambda^*, \nu^*)$.

The (4.9) is the constraint of Lagrange multipliers and (4.10) is the *complementarity constraint*.

The terms $g_i(\mathbf{x}^*) = 0$ have $\lambda_i^* \geq 0$ and are called active constraints, while those with $g_i(\mathbf{x}^*) > 0$ have $\lambda_i^* = 0$ and are called inactive constraints.

Therefore, to solve a problem of constrained minimization (like SVM), the steps, broadly, are:

- ▶ Ensure that the function to minimize is convex within constraints
- ▶ The constraints must generate a convex domain
- ▶ Calculate the primal Lagrangian
- ▶ Calculate the KKT conditions
- ▶ Replace the KKT conditions in the primal Lagrangian to obtain the dual Lagrangian (4.6)
- ▶ The minimum value of L_P it gets calculating the maximum value of L_D

Separator planes

To understand the proceedings, which leads to the definition of a separator plane that splits two classes such as in SVM algorithm, it is useful to introduce some mathematical notions.

- ▶ Given a vector $\mathbf{w} \in \mathbb{R}^d$, the equation

$$\mathbf{w}^T \mathbf{x} = 0 \quad (\mathbf{x} \in \mathbb{R}^d)$$

defines the plane π place of vectors \mathbf{x} orthogonal to \mathbf{w} .

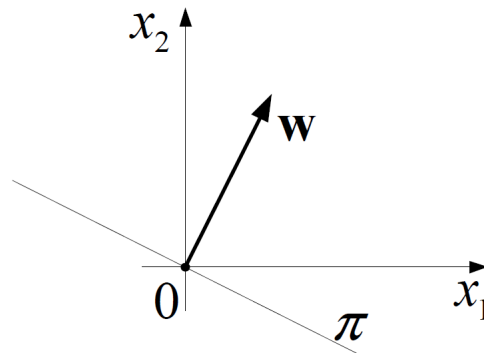


Figure 4.3: Plane π passing through the origin.

In the general case, if we translate the origin by a vector

a the equation becomes:

$$\mathbf{w}^T(\mathbf{x} - \mathbf{a}) = 0 \Rightarrow \mathbf{w}^T\mathbf{x} - \underbrace{\mathbf{w}^T\mathbf{a}}_b = 0 \Rightarrow \mathbf{w}^T\mathbf{x} + b = 0$$

► The distance of a point P from a plane π is:

$$\mathbf{P} = \mathbf{x}_p + d \frac{\mathbf{w}}{\|\mathbf{w}\|} \Rightarrow \mathbf{w}^T\mathbf{P} = \underbrace{\mathbf{w}^T\mathbf{x}_p}_{-b} + d\|\mathbf{w}\| \Rightarrow d = \frac{\mathbf{w}^T\mathbf{P} + b}{\|\mathbf{w}\|}$$

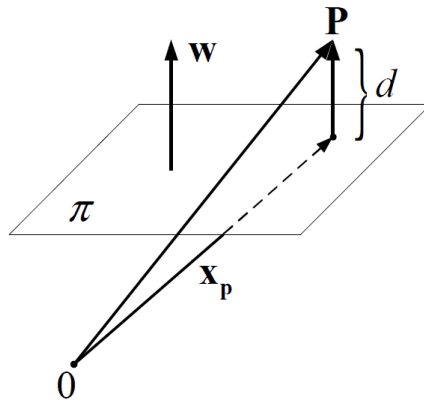


Figure 4.4: Distance d of a point P from the π plane.

It is important to note that the distance is a signed quantity: a point P' symmetrical at P respect to π has distance $-d$.

► Two parallel planes, π_a, π_b , have equations:

$$\begin{cases} \pi_a : \mathbf{w}^T\mathbf{x} + b = 1 \\ \pi_b : \mathbf{w}^T\mathbf{x} + b = -1 \end{cases}$$

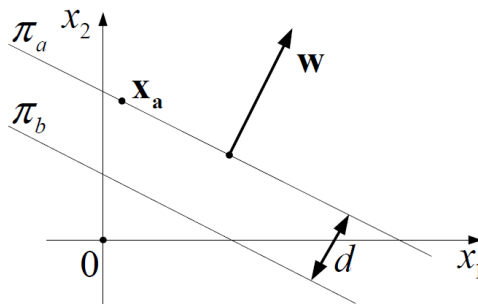


Figure 4.5: Distance d between two parallel planes π_a, π_b .

The distance d between this two planes can be calculated such as the distance of anyone point $\in \pi_a$ (for

example \mathbf{X}_a) from π_b . Therefore we have:

$$d = \frac{2}{\|\mathbf{w}\|}$$

- The π plane halfway between π_a and π_b has equation:

$$\pi : \mathbf{w}^T \mathbf{x} + b = 0$$

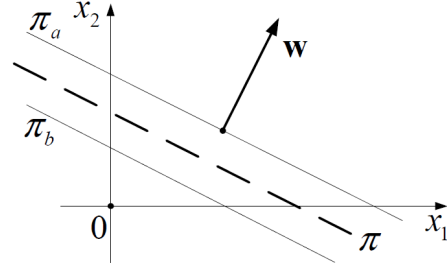


Figure 4.6: The π plane halfway between π_a and π_b .

- Points \mathbf{P}_a external to π_a with $d > 0$ satisfy the inequality:

$$\mathbf{w}^T \mathbf{P}_a + b > 1 \quad (4.11)$$

In the same way, points \mathbf{P}_b external to π_b with $d < 0$ satisfy the inequality:

$$\mathbf{w}^T \mathbf{P}_b + b < -1 \quad (4.12)$$

The inequalities 4.11 and 4.12 are the basic requirements to codify classes of points respectively marked by symbolic labels $+1$, -1 and separable from a plane π .

Linear Classifier, data linearly separable

We want to separate two classes of points $C1(\bigcirc)$ and $C2(\square)$, separable linearly, marked with symbolic labels $y = +1$ and $y = -1$ through a linear separator π like in Figure 4.7.

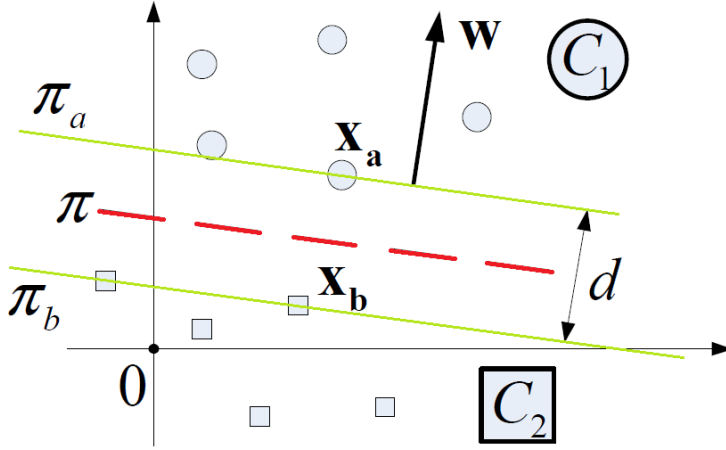


Figure 4.7: Classes of separable points C_1 , C_2 and separation region for a given \mathbf{w} .

There are many ways to divide these classes with a plane (generically hyperplane), but we want the one that maximizes the distance d between two support planes π_a and π_b .

Let's consider

$$y = \mathbf{w}^T \mathbf{x} + b$$

a generic plane function, where \mathbf{w} is a vector perpendicular to the plane and b indicates the translation of the plane in respect to the origin. The two support planes π_a and π_b are defined with the equations:

$$\begin{cases} \pi_a : \mathbf{w}^T \mathbf{x}^+ + b = +1 & (\mathbf{x}^+ \in C_1) \\ \pi_b : \mathbf{w}^T \mathbf{x}^- + b = -1 & (\mathbf{x}^- \in C_2) \end{cases}$$

Considering then $y^+ = +1$ the label of (\bigcirc) and $y^- = -1$ the label of (\square) , we can write:

$$\begin{cases} \mathbf{w}^T \mathbf{x}^+ + b \geq 1 \\ \mathbf{w}^T \mathbf{x}^- + b \leq -1 \end{cases}$$

If the domain of points is $D_n = \{(x_1, y_1) \dots (x_n, y_n)\}$, a general expression for the constraint, which applies to both classes, can be written as:

$$y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1 \quad \forall i \in \{1 \dots n\}$$

Knowing that the distance between π_a and π_b is $\frac{2}{\|\mathbf{w}\|}$, we want to find the parameters \mathbf{w} and b such that this distance is maximum:

$$\max_{\mathbf{w}, b} \frac{2}{\|\mathbf{w}\|} \iff \min_{\mathbf{w}, b} \frac{\|\mathbf{w}\|}{2}$$

To have only one solution of the KKT conditions (i.e. strong duality), the problem must be convex, namely:

- ▶ $\frac{\|\mathbf{w}\|}{2}$ must be convex. $\|\mathbf{w}\| = \sqrt{\mathbf{w}^T \mathbf{w}}$, so we have a square root that is NOT convex. One solution could be to take $\|\mathbf{w}\|^2$ instead of $\|\mathbf{w}\|$ which is convex and does not change the problem.
- ▶ The constraint must cause a convex domain. In this case the constraint is given by combinations of hyperplanes, so it is convex.

Definitely we have:

$$\min_{\mathbf{w}, b} \frac{1}{2} \|\mathbf{w}\|^2 \quad y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1$$

The primal Lagrangian is:

$$L_P(\mathbf{w}, b, \boldsymbol{\alpha}) = \frac{1}{2} \|\mathbf{w}\|^2 - \sum_{i=1}^n \alpha_i [y_i(\mathbf{w}^T \mathbf{x}_i + b) - 1]$$

Now the constraints become:

- ▶ $y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1$
- ▶ $\alpha_i \geq 0$
- ▶ $\alpha_i [y_i(\mathbf{w}^T \mathbf{x}_i + b) - 1] = 0$

The KKT conditions are obtained by doing $\nabla L_P = 0$, i.e.:

$$\frac{\partial L_P}{\partial \mathbf{w}} = \mathbf{w} - \sum_{i=1}^n \alpha_i y_i \mathbf{x}_i = 0 \rightarrow \mathbf{w}^* = \sum_{i=1}^n \alpha_i y_i \mathbf{x}_i$$

$$\frac{\partial L_P}{\partial b} = - \sum_{i=1}^n \alpha_i y_i = 0 \rightarrow \sum_{i=1}^n \alpha_i y_i = 0$$

Replacing these conditions on L_P we obtain the dual Lagrangian:

$$L_D(\boldsymbol{\alpha}) = -\frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j \mathbf{x}_i^T \mathbf{x}_j + \sum_{i=1}^n \alpha_i$$

Considering that $L_D(\boldsymbol{\alpha})$ is concave, it is immediate to reformulate the problem in terms of the convex $-L_D(\boldsymbol{\alpha})$:

$$\max_{\boldsymbol{\alpha}} L_D(\boldsymbol{\alpha}) = \min_{\boldsymbol{\alpha}} -L_D(\boldsymbol{\alpha}) =$$

$$= \min_{\alpha} \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j \mathbf{x}_i^T \mathbf{x}_j - \sum_{i=1}^n \alpha_i \quad (4.13)$$

subject to constraints:

$$\begin{cases} \alpha_i \geq 0 \\ \sum_{i=1}^n \alpha_i y_i = 0 \end{cases}$$

The (4.13) depends on data \mathbf{x}_i through the dot product $\mathbf{x}_i^T \mathbf{x}_j$. It is useful to consider these terms such as a symmetric matrix K :

$$K(i, j) = \langle \mathbf{x}_i, \mathbf{x}_j \rangle = \mathbf{x}_i^T \mathbf{x}_j = K(j, i)$$

The variables to know are the n α_i . Defined:

$$\boldsymbol{\alpha} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix}; \quad \mathbf{Y} = \begin{bmatrix} y_1 & 0 & \dots & 0 \\ 0 & y_2 & \dots & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & \dots & y_n \end{bmatrix}$$

the problem 4.13 can be written in this form:

$$\min_{\alpha} \frac{1}{2} \boldsymbol{\alpha}^T \underbrace{\mathbf{Y} \mathbf{K} \mathbf{Y}}_{\mathbf{Q}} \boldsymbol{\alpha} - \mathbf{1}^T \boldsymbol{\alpha}$$

that is a quadratic programming problem suitable for calculation routines.

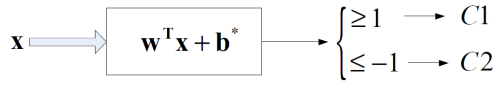
Once found the α_i we can observe that only few α_i are > 0 : these correspond to \mathbf{x}_i called "support vectors"; they are points closer to the separator hyperplane π and define π_a , π_b . Based on these $\alpha_i > 0$ we can calculate the separator parameters \mathbf{w}^* and b^* :

$$\mathbf{w}^* = \sum_{i=1}^n \alpha_i y_i \mathbf{x}_i$$

From complementarity constraint, for each support vectors \mathbf{x}_k ($\alpha_k > 0$), we have

$$b^* = y_k - \sum_{i=1}^n \alpha_i y_i \langle \mathbf{x}_i, \mathbf{x}_k \rangle$$

Definitely, given a new data point \mathbf{x} , to discriminate the class of belonging:



Linear Classifier, data not linearly separable

If we have classes that are not divisible by a hyperplane, we can, however, use a linear classifier considering some data points like errors due to noise.

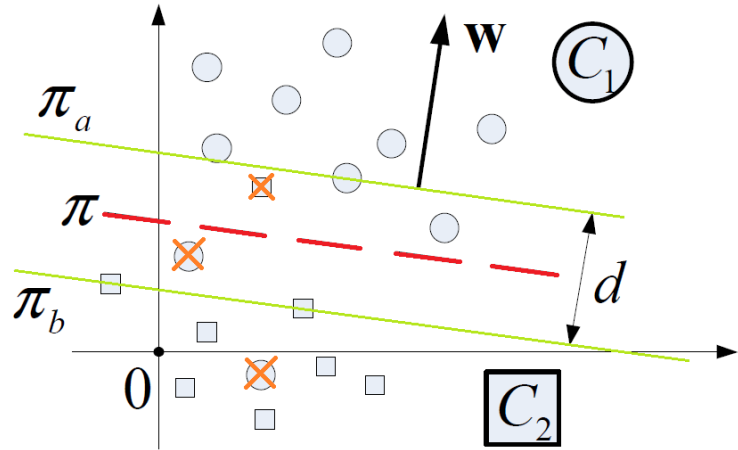


Figure 4.8: The orange crosses are wrong points that violate the constraints.

In such a way we must, sometimes, allow violation of constraints. This can be done introducing the *slack* variables ξ_i . In the present case, the problem of minimization becomes:

$$\min_{\mathbf{w}, b, \xi} \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^n \xi_i \quad \begin{cases} y_i(\mathbf{w}^T \mathbf{x}_i + b) - 1 + \xi_i \geq 0 \\ \xi_i \geq 0 \end{cases}$$

with C prefixed > 0 .

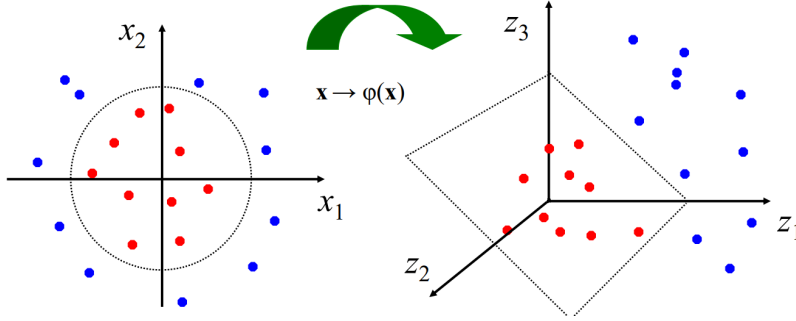
Without going into details the solution of this minimization problem is similar to the previous case, with the difference that the parameter b depends on both α and ξ .

Non-Linear Classifier, data not linearly separable

When data \mathbf{x}_i are not linearly separable, the classification can be obtained by a non-linear function; this implies passing from a space L of vectors \mathbf{x}_i to a space H :

$$\mathbf{x} \in L \rightarrow \phi(\mathbf{x}) \in H$$

then a linear separation can be done with points $\phi(\mathbf{x}_i)$. Usually the H space has dimension greater than L space. For example:



Where:

$$\underbrace{\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}}_{L=\mathbb{R}^2}; \quad \underbrace{\Phi(\mathbf{x}) = \begin{bmatrix} z_1 = x_1^2 \\ z_2 = \sqrt{2}x_1x_2 \\ z_3 = x_2^2 \end{bmatrix}}_{H=\mathbb{R}^3}$$

Considering the dot product $\mathbf{x}_i^T \mathbf{x}_j$, if we apply the non-linear function, the computational cost becomes big. Noting though that, in minimization problems, the primal (also dual) Lagrangian and the terms \mathbf{w} , b involving the data points \mathbf{x}_i only as dot product $\mathbf{x}_i^T \mathbf{x}_j$, we can take advantage of the so-called *Kernel Trick*. It consists of using kernel functions K , for which it is verified that:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$$

Not all kernel functions have this property; among those that have it some of the simplest and most common are:

► Polynomials:

$$K(\mathbf{x}_i, \mathbf{x}_j) = (\langle \mathbf{x}_i, \mathbf{x}_j \rangle + 1)^d \quad d = 1, \dots$$

► Radial Basis Functions (RBF):

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}\right) \quad \text{“Gaussian”}$$

So, instead of compute for each point \mathbf{x}_i its transformation $\phi(\mathbf{x}_i)$ having to pass in H, we calculate the dot product $\mathbf{x}_i^T \mathbf{x}_j$ directly with a kernel function, without therefore passing in

H. The function ϕ it can therefore remain unknown. For example, to determine the separator function we have:

$$f(\mathbf{x}) = \mathbf{w}^T \phi(\mathbf{x}) + b = \sum_{i=1}^n \alpha_i y_i \underbrace{\phi(\mathbf{x}_i)^T \phi(\mathbf{x})}_{K(\mathbf{x}_i, \mathbf{x})} + b$$

SVM for Exergames evaluation

The method presented below describes the SVM application used to provide a computer-assisted evaluation of the exergame sessions performed by the patient. A supervised classification method is used based on labeled data thanks to the support of clinical staff. The dataset consists of game sessions conducted under the therapist's evaluation, which labeled them as "Good" or "Other" while the patient was performing the tasks.

The method described below must be applied separately to each exergame, with appropriate adjustments due to the differences between them. In the next chapter, the experimental results will be presented as an application of this approach.

Note. Session duration

The most common duration of a single exergame session is 120 seconds. In particular, all those for motor rehabilitation –which constitute most of the ReMoVES catalog– have this duration. Exceptions are activities that reflect traditional tests with a pre-defined standard duration (such as Equilibrium Paint for the Sit to Stand, established at 30 seconds).

For this reason, the description of this method assumes 120 seconds (unless expressly mentioned otherwise).

During the data collection phase, exergames sessions are performed both by healthy subjects and by patients with different pathologies.

To define the dataset for supervised learning, we rely on the support of a therapist who assesses the performance of subjects in real-time during training with ReMoVES. A minimal web interface has been developed (also accessible from mobile devices) to facilitate this task. This tool includes two

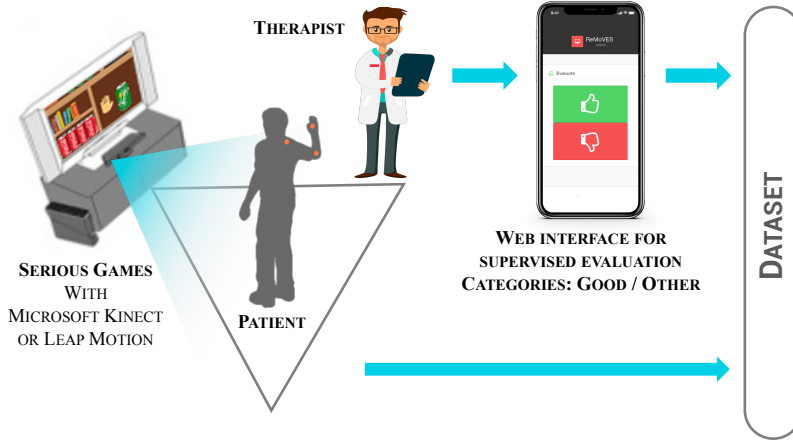


Figure 4.9: Dataset collection: the patient is performing an exergame using Microsoft Kinect as interface; the therapist interacts with a simplified interface to evaluate the patient training performance in real-time.

colored buttons (green and red) that the therapist can press at any time and several times, while the patient is performing the exercises (Fig. Ref fig: Setup). With the pressure of the green button, the period from the last evaluation will be labeled as a “Good” performance; on the contrary, pressing the red button will indicate the period as “Other”, which means that the patient did not perform the exercise correctly, regardless of the reason.

To increase the granularity, we decided to divide each session into segments; the segments are used as elements of the dataset, with the matching “Good” or “Other” label (Fig. 4.10).

The segment duration ranges between 2.0 and 20.0 seconds with 0.1 steps. In the next paragraphs the method that allows to select the most appropriate length is introduced while section 5.4 provides examples of results applied to ReMoVES exergames. As a result, up to 60 samples can be obtained from each session of 120 seconds:

$$t \in \{2.0, 2.1, \dots, 20.0\} \quad [s]$$

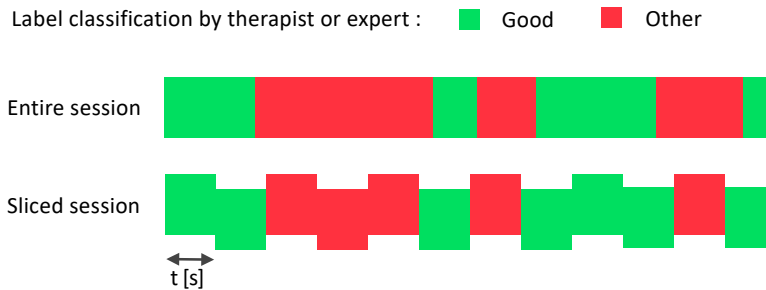


Figure 4.10: The session gets divided into segments of duration t . Each segment has a corresponding label for two-class classification: “Good” (in green) if the patient carried out the exercise correctly or “Other” (in red) if the patient performed poorly regardless of the reason.

1: LIBSVM is a popular open-source machine learning library, both developed at the National Taiwan University. The SVM learning code from LIBSVM is reused in other machine learning toolkits, including scikit-learn.

Model tuning

In the first instance, it is essential to choose whether to use a linear or non-linear SVM model. Similarly, the kernel function to be used must be defined. In general, it is possible to define the following criteria according to LIBSVM¹:

- ▶ if the dimensions of the space are large (for example, 2000 features), linear SVM is generally used: in a wide space, the samples are scattered, and even the simple hyperplanes are sufficient to separate the two classes. In this case, the only hyperparameter to set is C .
- ▶ if the size of the space is small (for example, 10 features), the main choice is non-linear SVM with RBF kernel. The hyperparameters to be set are C and γ .
- ▶ for average dimensional (for example, 200 features) in general, both types are tested.

It may therefore be considered appropriate to use a non-linear SVM with RBF kernel in the context of this study: no more than 20 features are extracted for each exergames and it falls within the case of a small dimensionality.

Parameters C and γ

Considering the minimization problem

$$\min_{\mathbf{w}, b, \xi} \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^n \xi_i$$

and the RBF kernel

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}\right) = e^{-\gamma\|\mathbf{x}_i - \mathbf{x}_j\|^2} \text{ with } \gamma = \frac{1}{2\sigma^2}$$

the only two parameters to set are C and γ .

C (> 0) is essentially a regularisation parameter and has the function of checking the penalty term, namely it controls the trade-off between achieving a low error on the training data, weighing errors more (large C , smaller-margin separating hyperplane), and low error on the future data (low C , larger-margin separating hyperplane). An example of the different settings of C is in Figure 4.11.

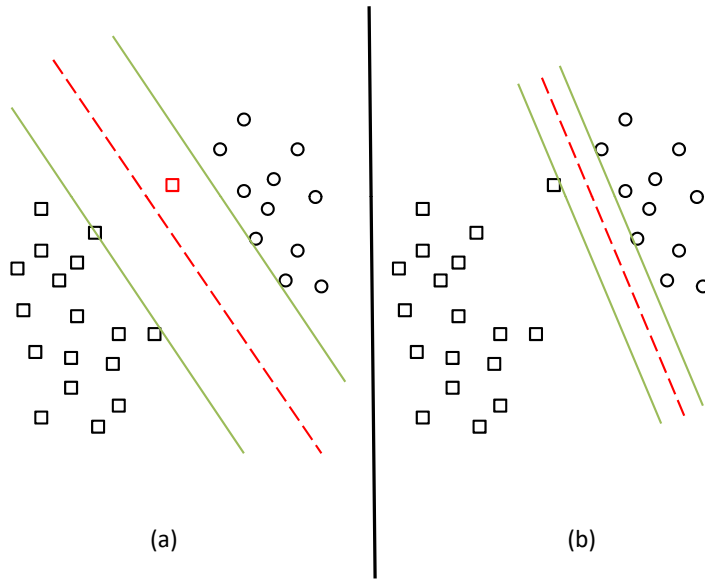


Figure 4.11: Low C (a) and large C (b).

Setting a large C results in a low error on the training set data, but the risk of future data errors is high (overfitting problem); conversely, low C results in more errors on training data (like the \square in (a) of Figure 4.11) but probabilistically fewer errors on future data. Practically the choice of C depends on the training set: if there are many noisy samples, it is better to set a low C .

The parameter γ defines the extent to which the influence of a single training example comes, so large γ means “close” influence (Gaussian with a small variance) and low γ means “far” influence (Gaussian with a large variance). An illustrative example is in Figure 4.12.

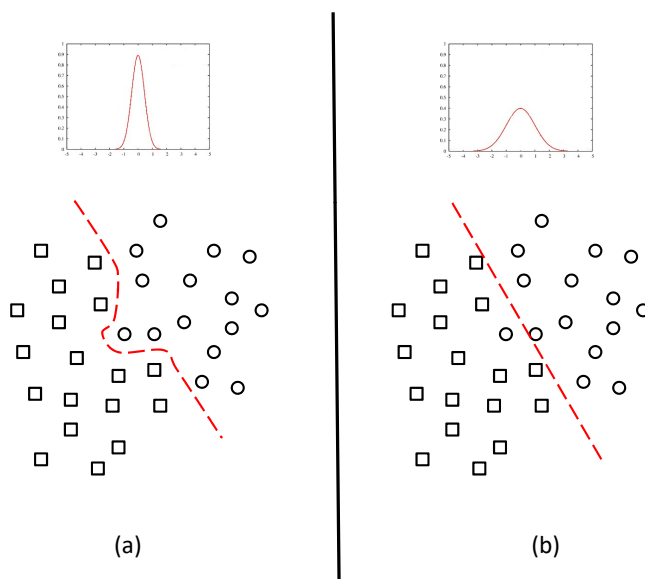


Figure 4.12: Large γ (a) and low γ (b).

With high values of γ , the training points near the decision limit are more important, while the points far from the decision boundary have less weight. On the contrary, with small values of γ , the distant samples weigh relatively more than the neighboring ones.

The goal is to identify good C and γ so that the classifier can accurately predict future data (e.g., testing data).

To get the best C and γ , a tuning process is required, but in our method this process is made more complex by the search for the segment size t . Therefore the procedure used to choose these parameters along with the best t selection, is the following:

1. Using default C and γ , the selection of t was made.
2. After having obtained t , C and γ tuning is performed.
3. Thus having best C and γ , the search for best temporal segment size t is performed again.

After some tests, we have found that the precise calibration of C and γ is almost irrelevant for our purpose of classification, moreover the best performances are obtained with their default parameters: $C = 1$ and $\gamma = \frac{1}{\#features}$.

Grid Search optimization

The main core of the method lies in the search for the best segment size t . As previously introduced, t may vary between:

$$t \in \{2.0, 2.1, \dots, 20.0\} \quad [s]$$

In the proposed workflow (Fig. 4.13), t is an hyperparameter that must be tuned according to the result of a “grid search” process.

For each t , the training set is used to train a specific model related to that segment length. Performance at any iteration is evaluated through 5-fold cross-validation.

It is necessary to evaluate the trend of accuracy as a function of t , even by drawing a graph. It is assumed that:

- for very low values of t : the data set consists of many but short segments; a fragment that is too short does not contain sufficient information on the movement and therefore is the classification “good” or “other” would be unfounded;

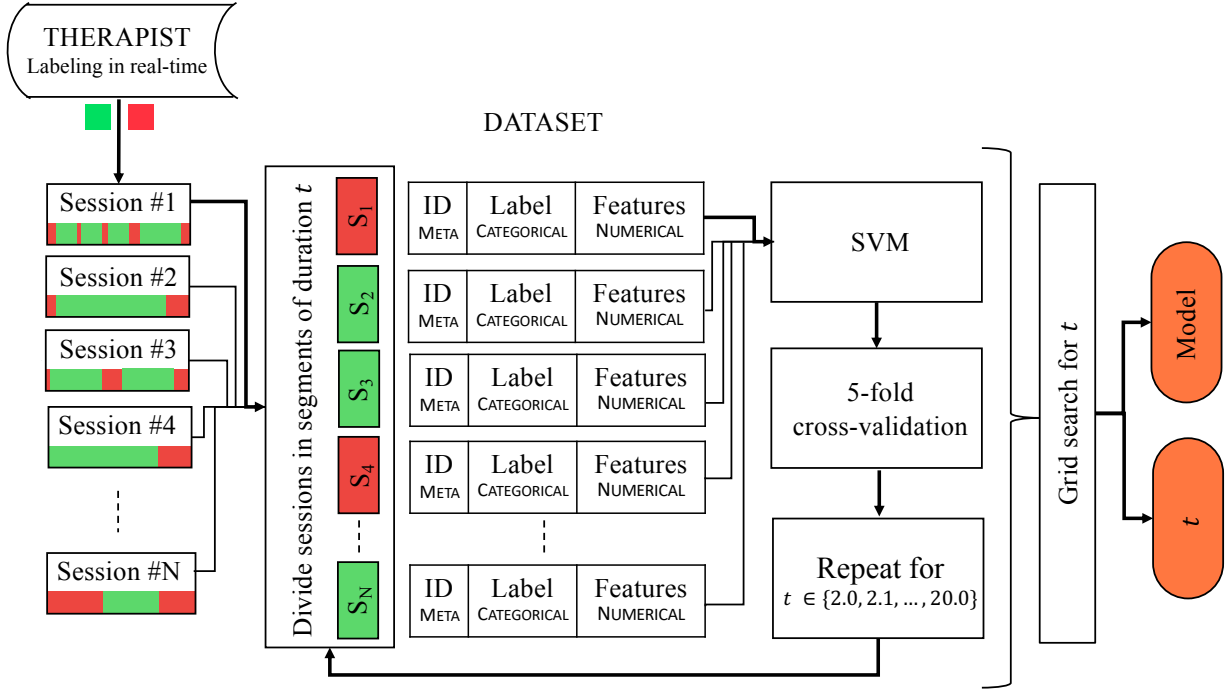


Figure 4.13: General flowchart about the SVM-based method. The model is trained with the sessions carried out by the subjects. Each session is divided into segments of duration t . The “grid search” optimization process allows the tuning of the hyperparameter t .

- for very high values of t : the data set consists of a few, but long segments; a fragment that is too long is not granular enough because it could contain both incorrect and correct movements.

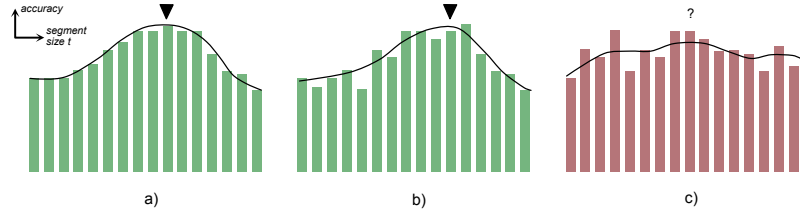
The SVM-based method based on the optimization of the hyperparameter t is successful only when it is possible to identify an optimal value of the size of the segments. In Figure 4.14c, it is not possible to identify an optimal t that offers better accuracy than the others.

In the real application, a polynomial fitting (black line in the figure) is applied to choose the optimal size of the segment t . According to when previously expressed, the curve is assumed to be a concave function, whose maximum represents a zone with better accuracy. Therefore, it is not always advisable to directly identify the maximum precision (as in Fig. 4.14a), but it may be necessary to look for the global maximum of the fitted curve (Fig. 4.14b)

Finally, the t selected in this phase will remain fixed for each future processing (it is recalled that each exergame will have its own t , which derive from separate stages of training and tuning of the SVM model). In other words, the t will be used

for the new data to be classified, coming from new activity sessions awaiting evaluation.

Figure 4.14: Optimization of the hyperparameter t through a “grid search” process. Three examples of possible configurations. In a) and b) it is possible to identify the maximum accuracy value through the fitted line; in c) the method is not applicable as the accuracy does not seem to depend on the segment size t .



The implementation of the proposed method relies on several tools provided by the “Scikit-learn” Python library.

K-fold cross-validation

The K-fold cross-validation is a technique for testing the model’s ability to predict new data that has been used in the training phase and t optimization to avoid problems such as overfitting. Typically, one performs k-fold cross-validation using $k = 5$ or $k = 10$, as these values have been shown empirically to yield test error rate estimates that suffer neither from excessively high bias nor from very high variance. In our method we are using $k = 5$ (Figure 4.15):

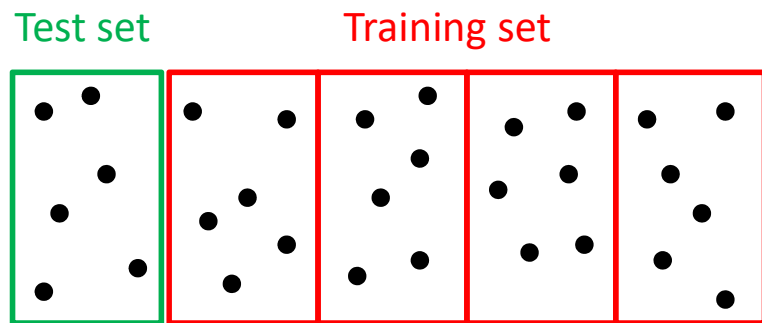


Figure 4.15: In the 5-fold cross-validation the dataset is divided into five groups, four for the training set and one for the test set.

Data in the training set are labeled with the belonging class and are used to train the model instead of data in the test set are considered as new data and are used to test the trained model.

The algorithm of k-fold cross-validation in pseudo-code is:

1. Divide the dataset into k groups
2. For i in range $(0, k-1)$

- a) Train the model using the $k-1$ groups of the training set
 - b) Test the model using the one group of the test set
 - c) Compute the accuracy and store it in a accuracyList
3. The final accuracy is obtained by

$$\frac{\text{sum}(\text{accuracyList})}{k}$$

Patient-specific model (optional)

Not used or employed in the current version of ReMoVES. We conceived the scenario in which the patient performs a considerable (over 30) number of sessions at the rehabilitation center under the supervision of the therapist before the release to home. In such a case, it is practical to build a patient-specific model based only on the sessions carried out by the patient, to use along with the general one.

Session evaluation

The evaluation of the training activity carried out by the patient (autonomously at his home) is the final goal of the platform. When a new exergame session is completed, the motion data is transferred to the ReMoVES cloud platform, where the analysis takes place. The session is divided into segments of duration t , which are evaluated on the basis of the general SVM model (plus the patient-specific model, if available). Each segment will have a (or two) predicted evaluation, belonging to the “Good” or “Other” classes. Finally, the segments are reassembled, and the overall evaluation of the whole session is generated on the basis of a weighted average (Fig. 4.16).

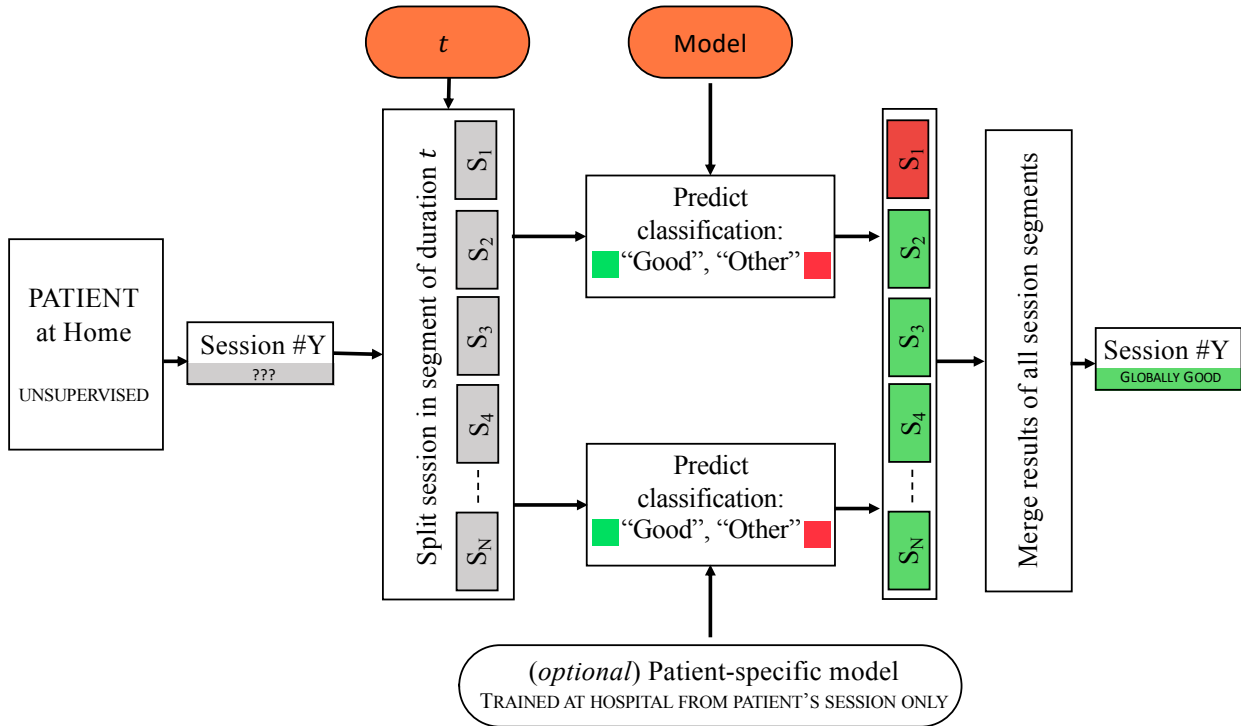


Figure 4.16: Evaluation of a new exergame session carried out by the patient at home, without the supervision of the therapist: it is divided into segments of duration t , which are evaluated on the basis of the general SVM model (plus the patient-specific model, if available). A weighted average provides the overall evaluation.

4.3 Method 3: Classification with LSTM

One of the main obstacles in the context of pattern recognition is the high dimensionality of data. This means that the number of training examples required by the training system is growing exponentially as the number of features available in the input increases. That is, given the number n of samples available, the system's predictive ability decreases as the number of features increases, with a consequent deterioration in performance.

This problem, known as the "curse of dimensionality," has meant that the approach typically used for pattern recognition is to divide the system into two modules: a feature extraction to reduce dimensionality, followed by the classifier.

The main problem of such an approach lies in the fact that the accuracy and precision of the predictions are strongly influenced by the ability of the person who creates the feature extraction module, which also requires a substantial engi-

neering effort and considerable knowledge of the system's application domain.

Deep Learning is a sub-category of Machine Learning that mainly allows the overcoming of this problem, through methods and algorithms of data representation in a hierarchical manner, on various levels of abstraction. The key aspect of Deep Learning lies in the fact that these levels of feature representation, to an ever-increasing degree of abstraction, are not designed and implemented directly by man, but are learned automatically from the data using special learning algorithms: the concepts at higher levels they are defined from those at lower levels through a series of non-linear transformations.

RNN

The so-called Recurrent Neural Networks (RNNs) is a type of architecture largely used today. Recurrent Neural Networks' concept is to use sequential input data. Usually, in neural networks, each input and output is believed to be independent of all others. Nevertheless, this hypothesis is not favorable for many types of issues. For instance, if you wanted to predict the next word in a sentence, knowing what precedes it is undoubtedly essential. The RNNs are called, indeed, *recurrent*, since they perform the same computations for all the elements of an input sequence, and the output of each of them depends on all previous calculations as well as the current input.

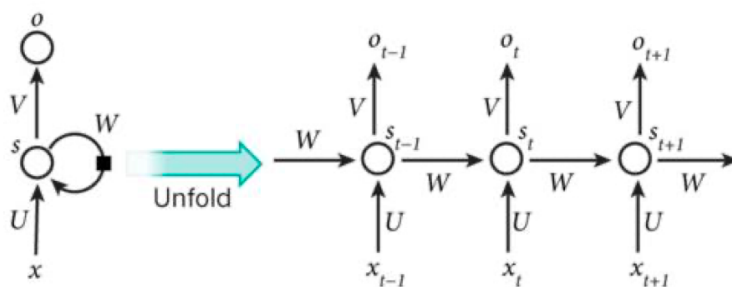


Figure 4.17: Unfolded and folded scheme of RNN.

The Figure 4.17 shows the aspect of a RNN, with its unfolded version, that is, explaining the structure of the network for the entire sequence of inputs, in different discrete and successive

The credits for the introduction to RNN goes to:
Nicola Capuano — Deep Learning.

moments. It should be noted that, differently from the typical multilevel neural networks, which use different parameters at each level, an RNN uses the same parameters, called U , V , W in the figure, at each time instant. Precisely, they carry out the same computation at every moment, on different inputs of the same sequence. Furthermore, sharing the same parameters dramatically reduces the number of parameters that the network must learn in the training phase, thus also improving training times.

Considering the unfolded version of the RNN, it is evident that, through the Back Propagation algorithm with only a small variation, it is possible to train networks of this type. Since the parameters are shared for each instant of time, the gradient calculated for each output depends not only on the computation at the current time instant, but also from the previous ones. For example, to calculate the gradient at a time instant $t = 4$ it is necessary to propagate the gradient calculation backward for the three previous time instants and then add the gradients thus obtained. An entire input sequence is typically considered to be a single element of the training set.

Therefore, the total error is simply the sum of the errors at each instant of time (for each element of the input sequence) and, consequently, the gradient of the error turns out to be the sum of the gradients at each instant of time. This procedure is called Back Propagation Through Time (BPTT). However, the training of this type of networks has proved to be affected by the so-called "vanishing/exploding gradient problem": in fact, the gradients that are calculated and propagated backward tend to increase or decrease at each instant of time and therefore, after a certain number of iterations, diverge to infinity or converge to zero.

With reference to the RNN illustrated in the previous figure, x_t is the network input at the instant t , which can be, for example, a vector representing a word within a sentence. s_t is the state vector of the network. It can be considered a sort of "memory" of the system, which contains information on all the previous elements of the input sequence. The state vector s_t is calculated starting from the current input and from the state vector in the previous instant, through the parameters U and W (matrices): $s_t = f(Ux_t + Ws_{t-1})$ where the function f is a non-linear function (for example \tanh or a Re-Lu), and o_t is the output of the network at the instant t , calculated

by the parameter V . The semantics of the network output will depend on the type of problem for which the network is used: for example, if we want to predict the word following within a sentence, it could be a vector of probability with respect to every word in the system vocabulary.

One of the main objectives of the Recurrent Neural Networks is to learn dependencies of the system output from the previous elements of the input. It has been verified that due to the aforementioned "vanishing / exploding gradient problem", such networks have difficulty learning and storing long-term dependencies (inputs and outputs far from each other). Various modifications and extensions of the basic RNN model have been proposed to overcome this problem. One of these is represented, for example, by Long Short Term Memory (LSTM) networks, whose basic idea is to improve the network by providing it with explicit memory. The LSTM networks, although not essentially having a different architecture from the RNNs, are equipped with special hidden units, called memory cells, whose behavior is to remember the previous inputs for a long time (Fig. 4.18). These cells take the previous state and the current input of the network as input at any time. Combining them with the current content of memory, and deciding by means of a gating mechanism through other units what to keep and what to erase from memory, have proved to be very useful and effective in learning long-term dependencies.

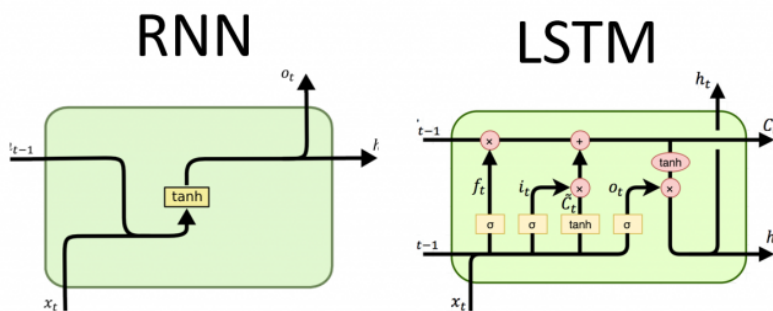


Figure 4.18: Long Short Term Memory (LSTM) networks is an extensions of RNN with additional hidden units used as memory.

5.1 Clinical Trials

Participants

The study is conducted at “Centro di Riabilitazione, Gruppo Fides Genova, Italy”, “Ospedale San Martino Padiglione Maragliano, Genova, Italy” and “Fondazione Don Carlo Gnocchi, Marina di Massa, Italy” while the data analysis is carried out at Department of Naval, Electric, Electronic and Telecommunications Engineering (DITEN), Università degli Studi di Genova, Italy. Written informed consent was obtained from patients who matched the eligibility criteria and participated in the trial. The patients are uniquely marked by a numerical code to make the data collected on the ReMoVES database anonymous. All the subjects followed the traditional rehabilitative treatment in the therapeutic plan defined by the clinical staff. The exergames performed with the ReMoVES platform should not be considered as a substitute for traditional rehabilitation but as an integration for entertainment and evaluation purposes. Baseline assessments have been recorded in order to collect medical, neurological, and psychiatric information.

The following inclusion criteria were applied:

- ▶ at least one of the following conditions:
 - frail elderly;
 - neurological sequelae of stroke (within 3 months after the acute episode);
 - neurological disorders;
 - post-surgery recovery following femur, hip, shoulder, radius, humerus, coastal fracture (or similar);
 - short-term complications (injuries, traumas) following fall episodes due to limited balance control;
- ▶ Mini-Mental State Examination (MMSE) greater than 22 points;
- ▶ Modified Barthel Index (MBI) of at least 35 points;

- ▶ active abilities of shoulder abduction (60° ROM) and elbow flexion-extension ($30^\circ - 130^\circ$ ROM) in one body side (required only for motion rehabilitation exergames);
- ▶ able to stand for 30 seconds with or without walking aids (required only for Equilibrium Paint exergame);
- ▶ willingness to participate in the study.

While these are the exclusion criteria:

- ▶ 5 points on a pain rating scale at rest;
- ▶ 4 or 5 points on Modified Ashworth Scale;
- ▶ manifest severe heart diseases like cardiac insufficiency;
- ▶ red-green color blindness.

The population of patients participating to this study consisted of 16 persons, with 7 male and 9 female patients. The average age of the whole population is 81.36 ± 6.79 years and age ranging from 70 to 91. The average age in the male population is 83.43 ± 4.83 and age ranging from 79 to 91. The average age in the female population is 79.78 ± 7.90 years and age ranging from 70 to 88.

The average MMSE, Tinetti Index (TI), and MBI of the whole population are respectively 25.15 ± 1.84 , 17.44 ± 5.46 , and 68.73 ± 16.69 . As for the male population, the average MMSE, TI, MBI are respectively 24.47 ± 1.78 , 19.05 ± 3.36 , and 73.83 ± 15.41 , while, regarding the female population, the corresponding indicators values are respectively 25.67 ± 1.81 , 16.29 ± 6.60 , and 64.36 ± 17.63 . For patients with standard indices at both the admission and discharge, the mean values between the initial and the final score have been used to compute the previous averages, otherwise only the starting indices have been considered in the calculation. Additionally, 8 healthy subjects were included in the study to collect comparison data. Participants characteristics are resumed in Table 5.1.

Table 5.1: Patients and healthy subjects in our study. General information is given in the first three columns. IDs are internal from the system Database and not necessarily in sequence (due to test, administration, or canceled accounts) The diagnosis is described in the fourth one. Fifth, sixth and seventh column contain respectively Mini-Mental State Examination (MMSE), Tinetti Index (TI) and Modified Barthel Index (MBI) values at the beginning and at the end of the hospitalization. The last three columns show the number of sessions in the database for each of the analyzed games. The total number of game sessions is 274.

ID	AGE	GNDR	DIAGNOSIS	MMSE	TI	MBI	OWL NEST	SHELF CANS	EQUILIBRIUM PAINT
29	71	F	Right sided weakness after ischemic stroke; Left side periprosthetic hip fracture.	27.1 -	15.5 - 17	71 - 75	NaN	2	NaN
31	91	M	Left pertrochanteric fracture.	24.2 - 24.6	12.5 - 16	71 - 75	10	10	7
33	83	M	Cerebral leukoaraiosis; Gait unsteadiness.	22.4 -	20 - 22	73 - 76	3	3	NaN
35	79	M	Left pertrochanteric fracture.	26.2 -		47 -	13	13	2
36	88	F	Chronic obstructive pulmonary disease (COPD); Mild scoliosis; Mild heart failure.	26 - 27.8	18.5 - 21.5	78 - 97	8	8	7
37	85	F	Left femoral neck fracture; Left sided weakness after a stroke.	23.5 - 25	15.5 - 18	50 - 60	5	6	NaN
38	80	M	Right shoulder fracture; Chronic obstructive pulmonary disease; Mild heart failure.	24.7 -	22.5 -	94 -	6	6	3
50	70	F	Mild cognitive impairment; Visuo-spatial left sided neglect after ischemic stroke.	25 - 26			10	8	NaN
52	83	M	Recent craniotomy for subdural hematoma; Polymorbidity.	27.1 -	15.5 - 18.5	71 - 75	12	14	5
53	70	F	Left side pertrochanteric fracture; Difficult standing.	24.8 -	14 - 16	35 - 47	2	2	NaN
57	89	M	Right radius fracture; Healed right hip fracture; Polymorbidity.	22.3 -			2	2	NaN
58	88	F	Right femoral neck fracture; Diffuse arthrosis.	22.2 - 23.8	14.5 - 17.5	60 - 74	NaN	2	NaN
60	85	F	Left femoral neck fracture; Previous right humerus, and femur fractures; Previous C2 vertebra fracture.	29.1 -	14 - 21	46 -	8	8	NaN
61	79	M	Right side mild hemiparesis; Right radius fracture; Polymorbidity.	23.3 - 25.2	18.5 - 22.5	75 - 88	10	12	5
62	76	F	Left fibula fracture; Left ischio-pubic fracture; Right shoulder arthrosis.	25.7 -			8	10	NaN
64	85	F	Neck pain from vertebral compressive fractures; Lower limbs arteriopathy; Chronic obstructive pulmonary disease (COPD).	24.7 -	25 - 27	76 - 86	4	4	NaN
25	29	M	Healthy subject				NaN	NaN	8
26	26	M	Healthy subject				NaN	NaN	6
40	27	M	Healthy subject				NaN	NaN	1
59	32	M	Healthy subject				NaN	NaN	4
71	41	M	Healthy subject				NaN	NaN	1
106	29	F	Healthy subject				NaN	NaN	6
107	26	M	Healthy subject				NaN	NaN	6
108	24	F	Healthy subject				NaN	NaN	2

5.2 Database release

As introduced in the 2 section of Chapter State of The Art, there is a deep scientific interest in this field. However the publications that provide the raw data acquired during the execution of exergames were not found. The substantial lack of available data limits the development of assistive computing technologies based on exergames, affecting both the technical aspect and the scientific innovation of the results. In particular, the possibility of comparing body tracking methodology (e.g., articulations to track; frequency), data transfer solution (e.g., client-server architecture or local storage only) and data-log format (e.g., JSON or CSV) is hindered. Furthermore, the impossibility of accessing the data collected in numerous studies proposed by the scientific community in recent years precludes the use of big data processing algorithms, thus yielding the scientific community to satisfy the need for publicly accessible databases. Aiming to overcome this limitation, this section describes the ReMoVES DB1 database released with this publication. It is available for download on Bitbucket (<https://bitbucket.org/numipditen/removesdb1/>, or mirror <https://www.numip.it/removesdb1>) and contributions from the research community are encouraged. Data is licensed under the Creative Commons Attribution 4.0 International license (CC BY-NC-SA 4.0)

The content is structured as follows:

1. in the main directory, there is a Comma Separated Value (CSV) file named *patients.csv*, which summarizes the patient's details, reflecting the contents of the Table 5.1.
2. in the main directory, there is a Structured Query Language (SQL) named *removesDB1.sql* with schema and data to create and populate a MySQL database.
3. the folder named *removesDB1* contains a set of CSV files representing the exact contents provided by *removesDB1.sql*, useful to import the data into different database systems or spreadsheet software.
4. the folder named *sessionlog* contains a structured collection of JavaScript Object Notation (JSON) files, each of them containing the data gathered during the execution of a session via ReMoVES. The file name corresponds to the *sessionid* provided in the database.

A more in-depth description of the contents of the *sessionlog* folder and information regarding the structure of the JSON files are presented. JSON files are grouped by exergame name and patients (subfolder named as the patient ID). Each JSON file consists of an array that collects temporal events. In each element of the array there are key-value pairs that provide the data. In order to provide a data set for future benchmarks and encourage scientific dissemination, the ReMoVES DB1 database is made up of mere raw data. In this way, researchers can conduct their customized studies directly on the data tracked by the ReMoVES system without intermediate pre-processing.

5.3 Method 1: Data Analysis

The results described in this section are related to the application of Method 1 introduced in 4.1. The reader is invited to understand the most significant indicators of the exergames. This section is essential to show how the results are presented to clinical staff. The therapist needs both graphs describing the performance of the patient's performance and summarized data that can give an objective and summary evaluation of the rehabilitation session. Providing an example related to motor rehabilitation, both the temporal plot of the angle of a specific articulation and a single numerical indicator of the ROM are required. Finally, this section is preparatory to the next paragraph where these indicators will constitute the vector of features used by the classification model too.

Upper Limb

Microsoft Kinect V2 was deployed in this analysis: the patient interacting with digital games was encouraged to reach an on-screen target with the arm motion (reaching task) in order to collect a high in-game score. The main movements at the shoulder joint (glenohumeral joint) tracked during the execution of functional exercises were: Flexion–Extension and Abduction–Adduction. During the execution of the rehabilitation exercise, we extract a large amount of data, but we are currently focusing on these features for the upper limb:

- **Score:** the score collected in-game is an abstract quantity associated to the player performance for their achievements. It acts as a quantitative indicator of success in the game introduced to motivate patients to attain a better score than their opponents/themselves. The *Score* feature is the ratio between the score collected by the user and the theoretical maximum achievable in the game:

$$Score = score_{user} / score_{max}. \quad (5.1)$$

- **Hand trajectory:** analysis of the hand trajectory is an indicator of the precision and the movement control level that the patient can keep during the activity. We calculate the distance between the trajectory (N samples over time $hand_i = (x_i, y_i)$, where x and y are the horizontal/vertical coordinates of the coronal plane) and the shortest line passing through the two points of $target = (x_t, y_t)$ (target spawn position) and $origin = (x_o, y_o)$ (Figure 5.1b):

$$d = \frac{1}{N} \sum_{i=1}^n \frac{|(y_t - y_o)x_i - (x_t - x_o)y_i + x_t y_o - y_t x_o|}{\sqrt{(y_t - y_o)^2 + (x_t - x_o)^2}}. \quad (5.2)$$

- **Compensation:** compensation is an undesired movement strategy adopted by the patient during the execution of the exercise. In detail, the distance d between the hand and the shoulder (Figure 5.1a) while performing the movement is evaluated in order to assess whether the patient reaches the targets by performing a correct Flexion–Extension or Abduction–Adduction movement or moves the whole body instead, implying that the hand-shoulder distance remains constant. Let us define μ the average of distances d_i with respect to the N observations during a single session; the *Compensation* parameter, index of the wrong movement, is then extracted as follows:

$$Compensation = -\sqrt{\frac{1}{N} \sum_{i=1}^N (d_i - \mu)^2}. \quad (5.3)$$

- **Barycenter:** this indicator deals with the detection and measurement of a spatial negligence in hemiparetic patients who ignore the targets that are offered to their attention in a certain part of the in-game space. Spatial

negligence affects approximately 30–40% of patients with acute stroke and consists of ignoring part of the space as a result of brain damage. The hand coordinates on the coronal plane, acquired over time, are used to populate a visual heatmap from which the therapist can evaluate the neglected areas; the spatial map is presented with a colour scale ranging from dark blue, where no movements were performed, to red, where there was the greatest occurrence (Figure 5.1c). This indicator is provided by the horizontal offset of the barycenter of the hand position observations over the session duration. In the evaluation of this indicator, it is also important to consider that in some variations of the OwlNest the targets are not equally distributed on both sides (e.g., to force a patient affected by left hemiparesis to focus his attention on the left side of the screen only).

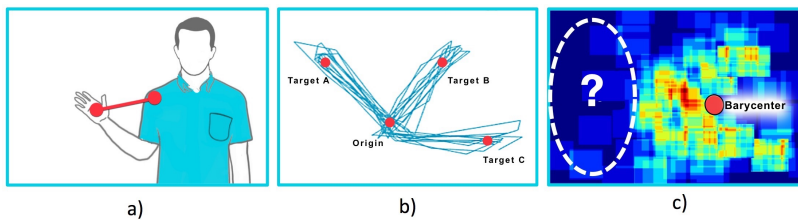
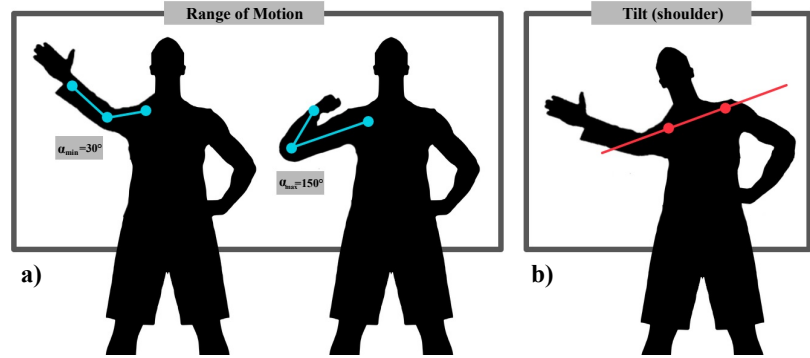


Figure 5.1: (a) *Abduction–Adduction* exercise scheme; (b) *Hand trajectory* in ShelfCans game; (c) Heatmap to detect neglected areas.

- **Range Of Motion:** the normal range of motion of the elbow is approximately 0 of extension and 140 of flexion. Most of the activities of daily living can be accomplished with 100 degrees of elbow flexion (from 30 to 130 degrees) [92]. The Range Of Motion feature is the difference between the maximum and minimum angle calculated with the Wrist, Elbow and Shoulder coordinates in 3D space (Fig. 5.2a).
- **Tilt:** lateral flexion (or side bending) is one of the fundamental trunk movement and it is normally defined in the 0 ± 35 degrees range. However, specifically for the Shelf Cans exergame this is an undesired movement strategy adopted by the patient during the execution of the arm flexion–extension and abduction–adduction exercise (Fig. 5.2b).
- **Twist:** trunk rotation on the transverse plane is a movement whose range is normally 0 ± 45 degrees. However, specifically for the Shelf Cans exergame this is a compensatory motion that the patient should avoid during

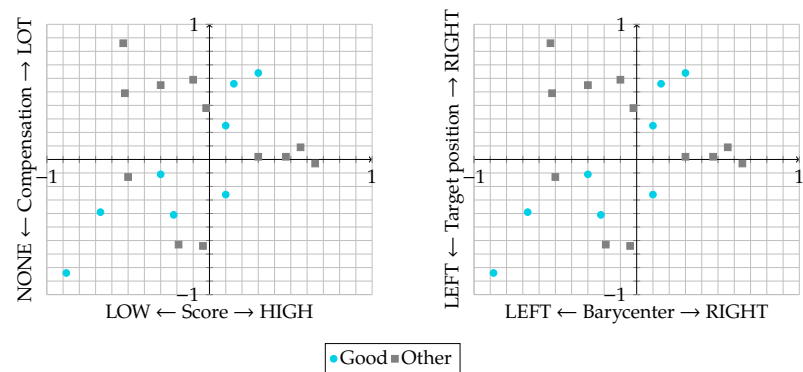
the execution of the exercise in order to exclusively train the arm and the shoulder.

Figure 5.2: a) Range of motion at elbow joint during flexion–extension and abduction–adduction exercise; the subject’s trunk is straight. b) Undesired compensation motion in Shelf Cans exergame: lateral flexion of the trunk.



In the OwlNest game, we are evaluating these relations: *Score–Compensation* and *Barycenter–Target positions* (Figure 5.3). In the former case, a good performance is achieved with a high *Score* and low *Compensation*. In the latter, a good performance is achieved when there is a linear dependency between the position of the hand and the position where the target on the screen spawned. With this analysis, we can discern when a shift from 0 in the *Barycenter* feature is caused by the patient’s syndrome or just by a bias in the positions where in-game targets (the coloured owls) are generated. For example, when most of the targets are generated in the left part of the screen, it is totally correct to collect a negative (left) *Barycenter* value and this is not an evidence of spatial negligence.

Figure 5.3: Plot of *Score–Compensation* and *Barycenter–Target position* features in OwlNest game. Data were labelled as “Good” or “Other” by the therapist according to patients’ performance.



For the ShelfCans game we are evaluating the relations: *Score–Compensation* and *Hand trajectory–Compensation* (Figure 5.4). The first case was already depicted for the OwlNest game. The latter highlights good performances when the hand follows a straight trajectory matching the shortest path

as much as possible, while the functional exercise is carried out without strategies of compensation.

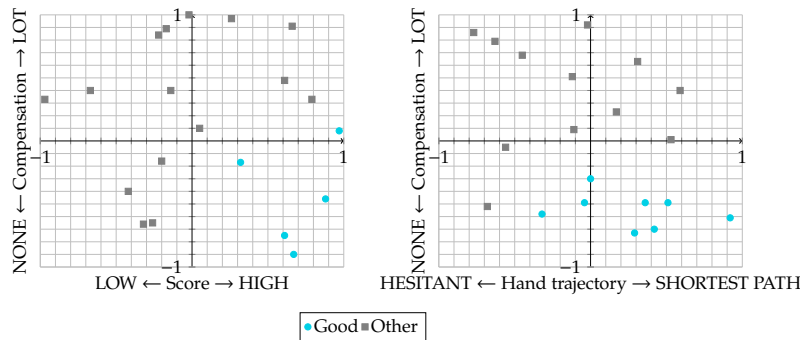


Figure 5.4: Plot of *Score–Compensation* and *Hand trajectory–Compensation* features in ShelfCans game. Data were labelled as “Good” or “Other” by the therapist according to patients’ performance.

Owl Nest: real patient analysis

This study begins with the discussion of the learning curves by patients. Table 5.2 lists the in-game scores rewarded to the patients over time: two separate rows –labeled with “R” and “L” for right and left arm respectively– are provided when both limbs have been trained. Empty cells are used to preserve the information of the alternation between the two body sides in the sequence of the sessions. In Figure 5.5 the same data of Table 5.2 are proposed as percentage increase and subsequently averaged. From this general chart, the experience perceived by the patient during the execution of consecutive trials can be assumed:

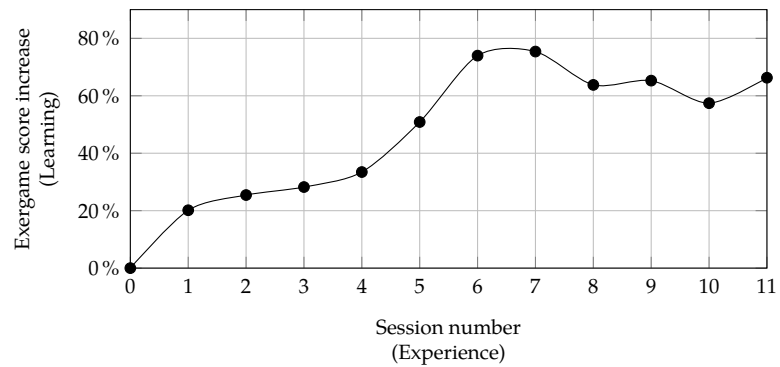
- ▶ the first five sessions are required by the patient to learn the game-play mode and get used with Microsoft Kinect interface: the most noteworthy increase occurs between the initial and subsequent sessions;
- ▶ in the three subsequent sessions the patient is driven by a strong motivation and is able to considerably increase the performance in the proposed activity: it can be assumed that the exergame and the level of difficulty proposed are suitable for the physical and cognitive conditions of the patient;
- ▶ in final sessions, the score is settled: the exergame level is no longer stimulating for the patient, demonstrating the importance of being able to modulate the difficulty of the activity.

The cognitive state of the patient, measured by the MMSE, is correlated with the performance in the game, as shown in Figure 5.6, in detail:

Table 5.2: Owl Nest exergame: scores obtained by users in the temporal sequence of exergame sessions. The patients who conducted the tests with both the right and left arm are represented in two separate rows (identified by “L” and “R” in the second column) and empty cells are used to preserve the information of the alternation between the limbs over time.

ID		Owl Nest exergame: score progression											
50	R	2700	4500	4500	4200	4800	5100	5700	6000	5400	5400		
52	R	2700		4200		3900		5390		4190		5090	
52	L		3300		3900		2100		5390		5090		5090
61	R		4500	4200		5990		5990		7190			
61	L	4200			3600		7190		6590		7490		
36	R	4500	5100	4200	5400	5690	7190	8090					
31	R	3300	3900	3300	3900	4200	5700	5690	5990	5690			
35	R	4200	6000		7200		6000		6600		5400		7490
35	L			5700		6900		6600		7500		7200	
62	R	4800		6900		8690		9890					
62	L		6300		8100		9890		10790				

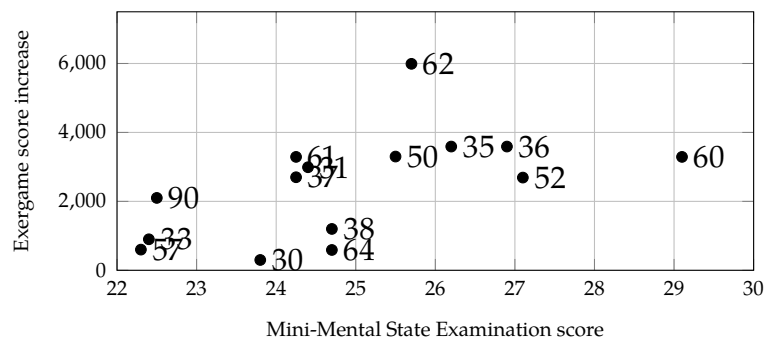
Figure 5.5: Owl Nest exergame: learning curve based on patient average. On the vertical axis is measured how the game performance comes from greater experience (the horizontal axis represents the temporal sequence of exergame sessions). The game performance is defined as a percentage increase compared to the initial session.



- ▶ according to the inclusion criteria in 5.1, no patient has a MMSE score lower than 22;
- ▶ for patients who have been administered the test both at the admission and discharge, the average between the score is used;
- ▶ on the vertical axis there is the difference between the maximum score and the one in the first session: the aim is indeed to evaluate the increase with respect to the initial condition;

This analysis shows that patients with better cognitive abilities can learn the techniques and strategies to play faster, regardless of their physical conditions: they could benefit from subsequent levels of difficulty in the game.

Figure 5.6: Owl Nest exergame: scatter plot of the Mini-Mental State Examination score versus the maximum in-game score increase achieved by the patient, calculated as the difference between his overall best result and his first session. Each point is labeled with patient ID. The horizontal axis has the lower limit of 22 as per the inclusion criteria on MMSE.



In the following, the study focuses on the movement of the upper limbs taking as an example Patient 62, affected from fibula and ischio-pubic fractures. In addition to the main lower limb disease, this patient suffers from arthrosis of the right shoulder. The ReMoVES platform has confirmed superior performance of the healthy arm both in terms of in-game score and motor skill. Using the spatial coordinates –provided by Microsoft Kinect as in Figure 3.1– of the articulations 5, 8, 15 (for the right side) and 3, 6, 9 (for the left side), the ROM was calculated at the elbow joint. Patient 62 has a general improvement over time (Fig. 5.7a) and the maximum left elbow angle is always greater than the right one (Fig. 5.7b).

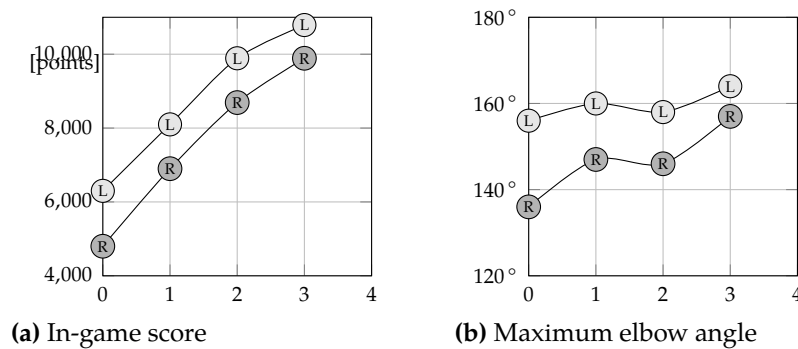


Figure 5.7: Owl Nest exergame: Patient 62. The patient suffers from arthrosis of the right shoulder. The in-game score and the movement performances (such as the ROM angles) on the healthy limb (left) are better. The horizontal axes represent the temporal sequence of exergame sessions.

Patient 38 –affected by right shoulder fracture– is now considered by comparison. In this case, the evaluation of the in-game score leads to negligible results (Fig. 5.8a), but an analysis of the extension of the limbs in all four directions (right, left, up and down) reveals better performance with the left arm (Fig. 5.8b). ReMoVES can therefore be used as a measurement tool, to provide the therapist with objective and automatic ROM assessments.

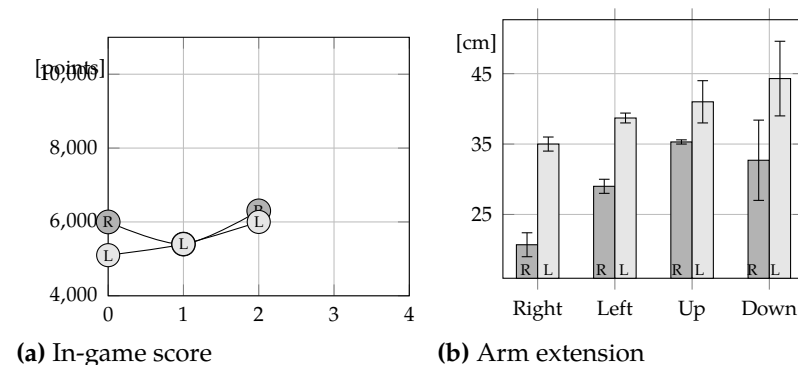


Figure 5.8: Owl Nest exergame: Patient 38. The patient fractured his right shoulder. The in-game score difference between the two upper limbs is negligible, while the extension of the left arm in all four directions is more pronounced.

Shelf Cans: real patient analysis

The resulting data show that the errors made by the patients in matching the tin can with the corresponding colored shelf are almost negligible and inconclusive, also due to the good MMSE score of the players. Some difficulties in recognizing the targets are present only in the sessions of patient 50, affected by hemispatial neglect.

In this study we used the Shelf Cans game to assess the accuracy of the movement leveraging on the Hand Trajectory provided in Equation 5.2. Figure 5.9 shows the evolution over time of the performance of Patient 62 with the impaired arm. Sessions 0 (the first), 2 (after five days), 4 (after nine days) and 8 (after about a month) are selected to show progressive improvement. For each session, the distance d is indicated, where lower values are better because they indicate a more precise path. Patient 62 becomes familiar with the Microsoft Kinect interface and manages to make the trajectories less and less confused: at the discharge time, the subject manages to control the arm movement with rather precise movements, always leading the can of soda towards the shelf of the corresponding color without hesitation.

Figure 5.9: Shelf Can exergame: Patient 62, right hand. Each point corresponds to the temporal position of the tin can on the screen: the color indicates the correct destination. The temporal evolution of the movement control is provided: in the last session the subject is more confident and delivers the tin can without much hesitation in the corresponding shelf as defined by the value distance d (lower values are better).

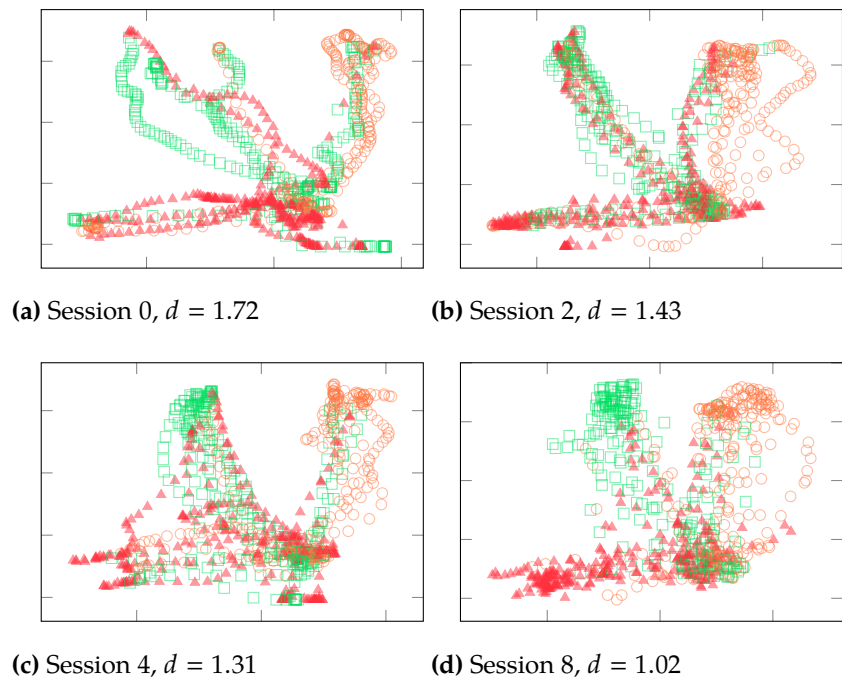
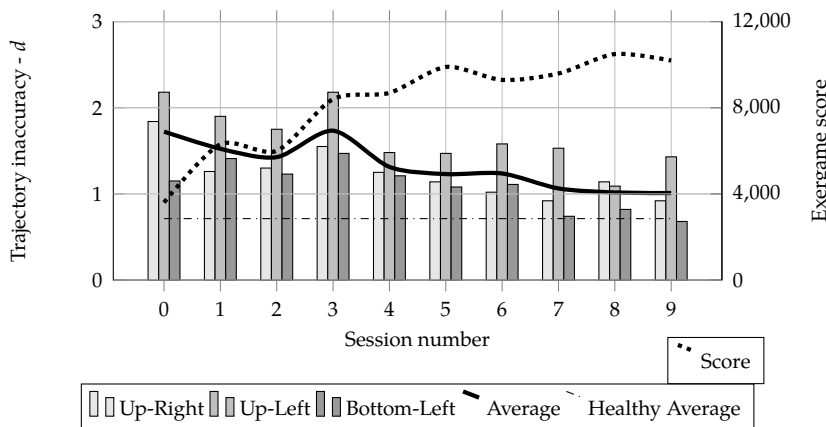
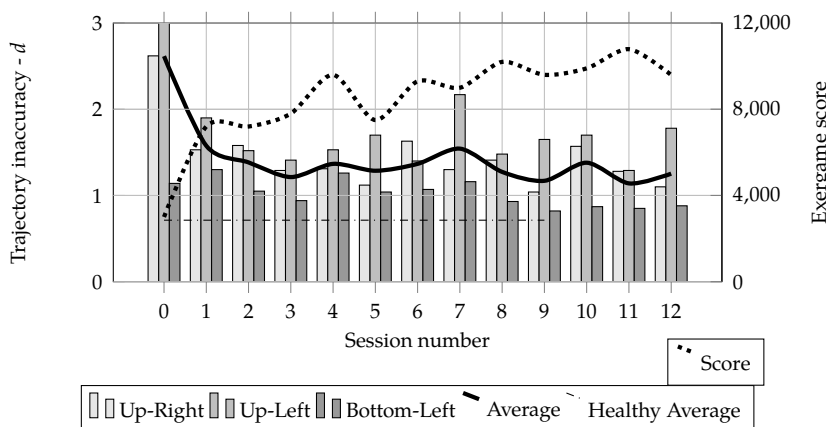


Figure 5.10 offers an overview of Patients 62 and 35 results. The former starts from deficient base but approaches the

performance of a healthy subject before discharging. In detail, she achieves a very substantial increase in the in-game score, going from 4,800-6,300 (sessions 0 and 1) to 9,890-10,790 (sessions 8 and 9), which are outstanding values (for reference, the maximum score obtained by a healthy and young person settles at around 12,000 points). Even the precision of the movement is enhanced: the distance falls (lower is better) from $d = 1.72 - 1.52$ (sessions 0 and 1) to $d = 1.02 - 1.01$ (session 8 and 9). Patient 62 improved her general psycho-physical state thanks to the rehabilitation program at the recovery center: ReMoVES allows quantitatively measuring this change while offering a welcome stimulus in the field of wellness for elderly patients. In comparison, the patient 35 –not suffering from any upper limb disease– does not significantly improve the accuracy of the movement: excluding session 0, necessary to gain confidence with the Microsoft Kinect interface, the results are already satisfactory even in the first session. It is interesting to note that patient 35 was able to improve his speed abilities to obtain an increasingly high in-game score, keeping the distance indicator d low.



(a) Patient 62



(b) Patient 35

Figure 5.10: Shelf Cans exergame: Patient 62 and Patient 35. Overview of patient performance. The movement precision is calculated with distance d (lower is better): a bins for each of the three shelf positions and the bold line for the average. The horizontal dotted line indicates the standard performance of healthy subjects. The score in the game is plotted by the dot line and refers to the right vertical axis.

Lower Limb

Microsoft Kinect V2 is deployed in this kind of activity. The user must accomplish the Abduction–Adduction movement with their impaired leg while they are standing. The therapist can suggest to the patient to hold on to a physical support, such as the back of a chair, in order to prevent falls or equilibrium instability. The elevation of the leg and additional body joint positions are tracked with the Microsoft Kinect V2 to detect the balance status of the user’s body: to accomplish the exercise correctly, the patient must keep the trunk erected and straight. During the execution of the Flappy Cloud rehabilitation exercise, we extract a large amount of data, but we are currently focusing on these features for the lower limbs:

- **Score:** same as previous activities.
- **Elevation:** it is the maximum elevation of the impaired leg calculated as the angle between legs during the Abduction–Adduction movement. The *Elevation* feature is the ratio between the maximum angle reached by the user and the maximum reached on average by healthy subjects:

$$Elevation = elevation_{user} / elevation_{healthy}. \quad (5.4)$$

- **Compensation:** to accomplish the exercise correctly, the patient must keep the trunk erected and straight. In this case, the angle between the patient’s trunk and the ideal vertical attitude is considered.

$$Compensation = \angle_{trunk, vertical}. \quad (5.5)$$

For the FlappyCloud game, we are evaluating these relations: *Score–Compensation* and *Elevation–Compensation* (Figure 5.11). The first case was already depicted for other games. In the latter case, a good performance is achieved when the patient collects high *Elevation* value during the Abduction–Adduction while keeping their trunk erected and straight.

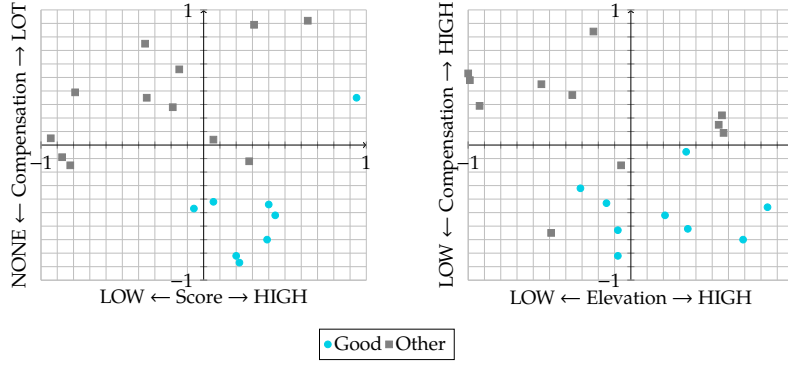


Figure 5.11: Plot of *Score-Compensation* and *Elevation-Compensation* features in the FlappyCloud game. Data were labelled as “Good” or “Other” by the therapist according to patients’ performance.

Sit to Stand

Patients are required to stand and sit as many times as possible in the given time (30 seconds), maintaining the correct symmetric position. In this section some particular movements, tracked via the exergame, are described. Movement analysis via ReMoVES system is personalized and makes it easy to explain some particular behavior related to the patient’s condition such as erroneous movements or compensation strategies. In the following, the influence of some specific diseases in the game performance is shown along with the way to recognize them. Then, initial and final performance are taken into consideration, searching for connections with the Tinetti Index and Modified Barthel Index score. To conclude, data are compared with game performance from healthy subjects and a method for the automatic evaluation of the activities is described. The following features were taken into account for Sit to Stand evaluation:

- **Repetition rate:** number of repetitions in a given time; it is proportional to the in-game score. The *Repetition rate* is the ratio between the rate maintained by the user and the average kept by healthy subjects:

$$\text{Repetition rate} = \text{rate}_{\text{user}} / \text{rate}_{\text{healthy}}. \quad (5.6)$$

- **Repetition trend:** the trend of the time required by the user to accomplish a single STS cycle. The analysis of the variability during a single session is, for example, important to detect the fatigue level of the patient. Given i the repetition number and t_i the cycle duration, the *Repetition trend* is the slope (m) of the linear regression of t_i with respect to i :

$$m, q = \text{LinearRegression}(i, t), \quad (5.7)$$

$$\text{Repetition trend} = m.$$

- **Coronal shift:** verification of the correct strategy used by the patient to stand up, considering the trunk tilt on coronal plane (Figure 5.12a). Even though the movement trajectory projected in the sagittal plane must show some forward/backward displacement, the correct coronal trajectory must be linear and constant around the zero value.
- **Shoulder tilt:** to accomplish the exercise correctly, the patient must stand up and sit down without twisting or tilting the shoulders. A correct movement provides very small angles of inclination with a tolerance of about 10 degrees, and therefore the average value must be around 0 degrees (Figure 5.12b).

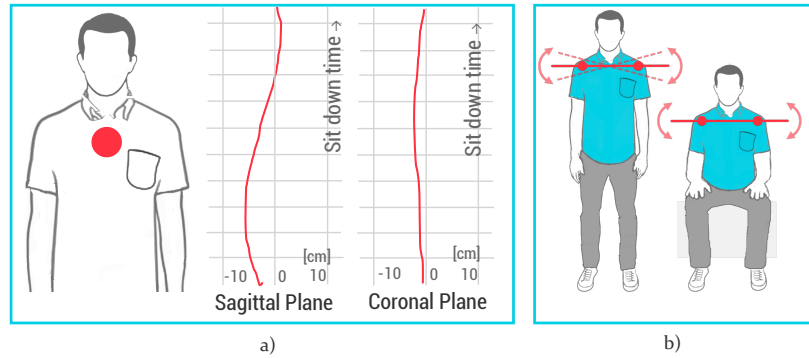


Figure 5.12: (a) Trunk tilt on sagittal and coronal planes; (b) Shoulder tilt detection.

For the Equilibrium Paint game, we are evaluating these relations: *Repetition rate–Coronal shift* and *Repetition trend–Shoulder tilt* (Figure 5.13). In the former case, a good performance is achieved when the patient collects high in-game Score while keeping the *Coronal shift* around zero during the STS exercise. In the latter, a good performance is achieved when the *Repetition Trend* remains constant (or even increases) during the whole session, while the average value of *Shoulder tilt* remains around 0 degrees.

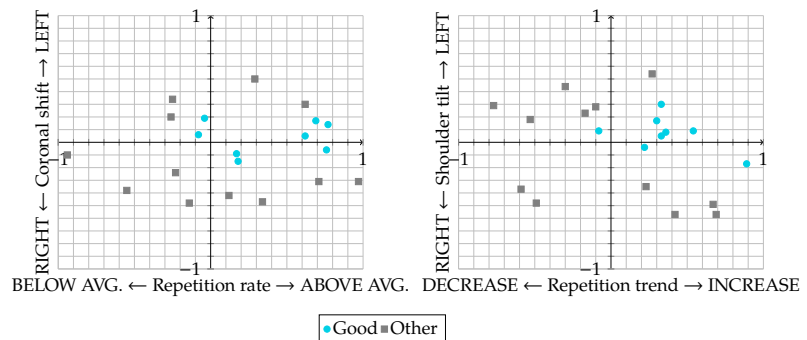


Figure 5.13: Plot of *Repetition rate–Coronal shift* and *Repetition trend–Shoulder tilt* features in the EquilibriumPaint game. Data were labelled as “Good” or “Other” by the therapist according to patients’ performance.

Equilibrium Paint: real patient analysis

Orthopedic diseases limit mobility and strength and therefore affect patients' movements. Patient 31 was under rehabilitation because of the broken left trochanter. In the ascending phase the lack of strength in the left leg influence the hips position, while in the descending phase the patient returns to the correct configuration. Figure 5.14 shows the patient's lateral displacement along the game session. The continuous line represents the position of the spine base (point 18, Figure 3.1) on the y axis. The background color is associated with ascending (bright gray), descending (dark gray) and resting (white) phases in the session. A brief cinematic analysis shows that, as a consequence of the patient's impairment, hips are displaced on the right in the ascending phase (positive values of the line in the bright gray background).

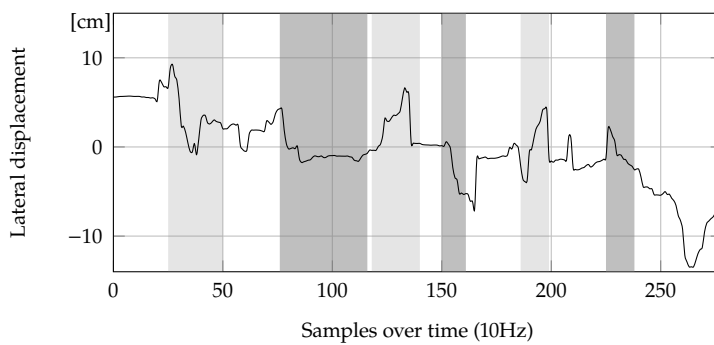
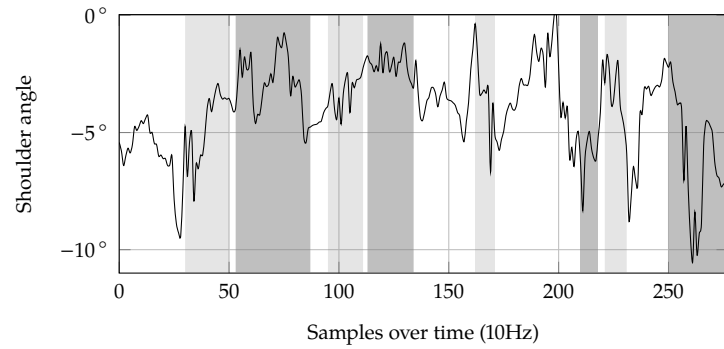


Figure 5.14: Equilibrium Paint exergame: Patient 31. Lateral displacement during the game session. Spine base horizontal position.

Patients practicing STS may adopt some erroneous movements or compensation strategies due to their impairments. Typically, they bend the trunk towards the weak limb so as not to burden it and shift the weight on the healthy leg.

However, in case of postural diseases, anomalous positions can be misunderstood as compensation strategies, but are actually the standard posture. It is thus very important to connect the diagnosis of patients to the game session analysis, thus they have been included in ReMoVES DB1. Patient 36 suffers from scoliosis and so her trunk results curved even at rest. Therefore, the left shoulder is correctly tracked higher than the right one from the beginning of the session. Figure 5.15 shows the values of the angle between the shoulders and the axial plane along the session.

Figure 5.15: Equilibrium Paint exergame: Patient 36. Shoulder angle in the coronal plane. Average angle: -3.51° .



General weakness in geriatric people is frequent and strongly affects also simple activities such as standing. Patient 52 is a frail elderly man who has suffered from chronic subdural right hematoma and currently is affected by polymorbidity. As a consequence, he is able to perform only a limited number of STS cycles in the given time and there are many recovery phases during the game session. Figure 5.16 and 5.17 (first and fourth session) show the movement of the spine base (point 18, Figure 3.1) along the z axis thus providing the number of sit-ups. The number of completed STS cycles and the long resting pauses did not change significantly even after a period of rehabilitation (Figure 5.17 refers to a game session held two weeks later than the one in Figure 5.16).

Figure 5.16: Equilibrium Paint exergame: Patient 52. Spine base vertical position along the first session. Long pauses and a single performed sit-up.

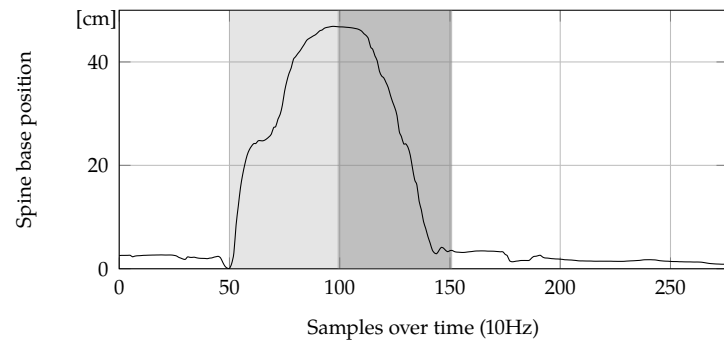


Figure 5.17: Equilibrium Paint exergame: Patient 52, spine base vertical position along the fourth session. Long pauses and limited number of sit-ups ($n = 2.5$).

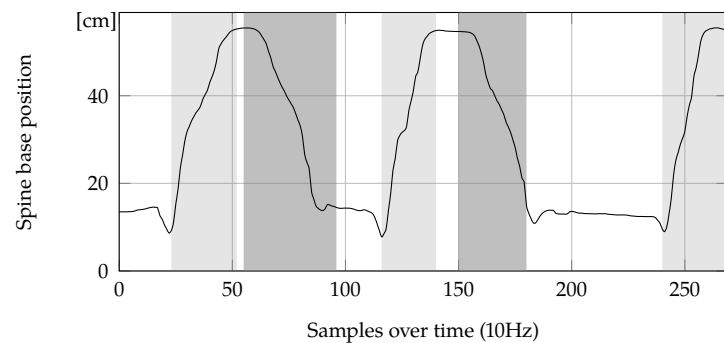


Figure 5.18 shows the tracked number of sit-ups performed by Patient 61 in the last session before he was discharged. In this case, no resting moments are present and the intermediate peaks (e.g. approximately at time 48s) are due to patient's impairment at sitting. This image is provided in order to compare the activity of a very frail elder (Patient 52) and another old man (Patient 61) who has deeply benefited from the rehabilitation process.

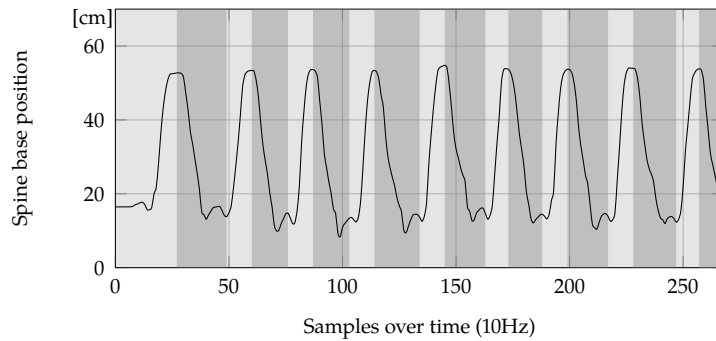


Figure 5.18: Equilibrium Paint ex-game: patient 61. Spine base vertical position along the session. Regular movement and good number of sit-ups ($n = 9$).

Limited mobility can also be a consequence of traumas or strokes. Patient 61 is affected by right hemiparesis, namely the right side of his body is very weak. A strategy that allows him to compensate his weakness is moving backward the right leg in order to put strength on the left lower limb. As a result, the whole body is rotated on the coronal plane. Figure 5.19 depicts the angle of the shoulders line within the axial plane.

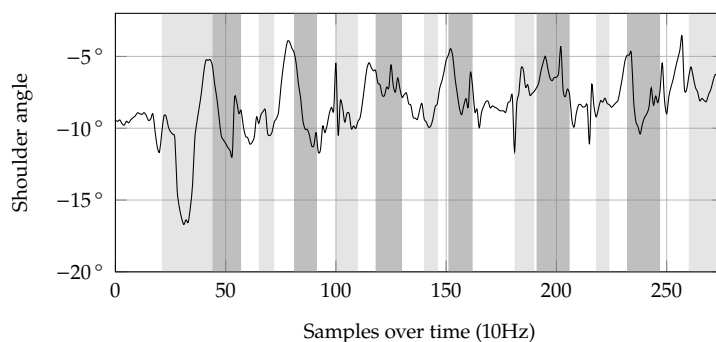


Figure 5.19: Patient 61: shoulder angle in the axial plane. Average angle: -8.07° degrees. The current game session is not the same as in Figure 5.18.

Equilibrium Paint: standard indices comparison

Data collected on several sessions denote a rehabilitation success for the previously described patients and the sit-up number increase gives evidence of an improvement of their conditions. Such data are coherent with the values of the

standard indices used in a rehabilitative context. Table 5.3 shows the values of the Tinetti Scale and modified Barthel Index of patients and the number of sit-ups in 30 seconds.

Table 5.3: Sit-ups number and indices values at the beginning and at the end of the hospitalization.

ID	31	36	52	61
Sit-Up Num - Admission	2	3.5	1	6.5
Sit-Up Num - Discharge	3.5	6.5	3	9
TI - Admission	12.5	18.5	15.5	18.5
TI - Discharge	16	21.5	18.5	22.5
MBI - Admission	71	78	71	75
MBI - Discharge	75	97	75	88

Even though a small population has been analyzed, a correlation between the number of sit-ups in 30 seconds and the patient's Tinetti index and modified Barthel index (Table 5.4) can be observed.

Table 5.4: Correlation values between sit-ups number and standard indices.

Variables	Correlation
SU vs TI - Admission	0.70
SU vs TI - Discharge	0.89
SU vs MBI - Admission	0.60
SU vs MBI - Discharge	0.75

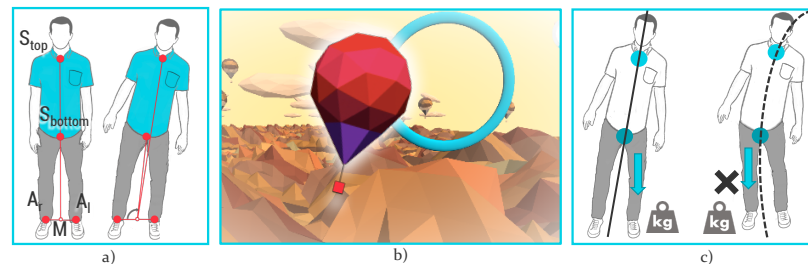
Medium/strong correlation between the number of sit-ups and the indices is proved. Furthermore, a strong correlation between the increase of sit-ups number (i.e. ΔSU) and the improvement of the MBI (i.e. ΔMBI) has been found:

$$\rho(\Delta SU, \Delta MBI) = 0.94 .$$

Balance Shift

The exergame focused on the balance shift functional exercise is Hot Air.

Figure 5.20: (a) Tracked joints for Center of Pressure (CoP) estimation; (b) Gameplay during a serious game session; (c) Erroneous balance shift detection.



Its main features are:

- **Score:** same as for upper limb games.
- **Center of pressure variation:** during the Balance shift functional exercise, the patient must load weight on the two legs alternately, and thus the variation of CoP on the mediolateral axis is calculated.

$$CoP_{variation} = -\sqrt{\frac{1}{N} \sum_{i=1}^N (CoP_i - \mu)^2}. \quad (5.8)$$

- **Compensation:** to accomplish the exercise correctly, the patient must alternate the load on the lower left and right limbs without compensating the movement by shifting the upper part of the body. This erroneous strategy can be detected by computing the difference between $Tilt_{bottom}$ and $Tilt_{top}$ (Figure 5.20c):

$$Compensation = Tilt_{bottom} - Tilt_{top}. \quad (5.9)$$

For the Hot Air game, we are evaluating these relations: *Score–CoP variation* and *CoP variation–Compensation* (Figure 5.21). In the first case, a good performance is achieved when the patient collects a high in-game *Score* while their effort in shifting the load between left and right limbs is high. In the second analysis, the correct performance is achieved with high *CoP variation* and low *Compensation*.

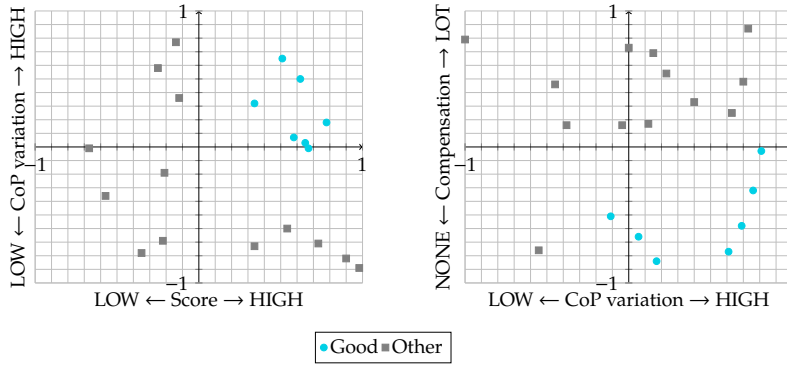


Figure 5.21: Plot of *Score–CoP variation* and *CoP variation–Compensation* features in HotAir game. Data were labelled as “Good” or “Other” by the therapist according to patients’ performance.

Hot Air: comparison with Wii Balance

The Nintendo Wii Balance Board (WBB) has already been validated as a suitable alternative to a laboratory-grade force platform in the measures of Center of Pressure (CoP) in contexts where a clinical assessment of balance is required without an elevated precision level [93, 94]. The ReMoVES platform does not employ the WBB despite its adequate

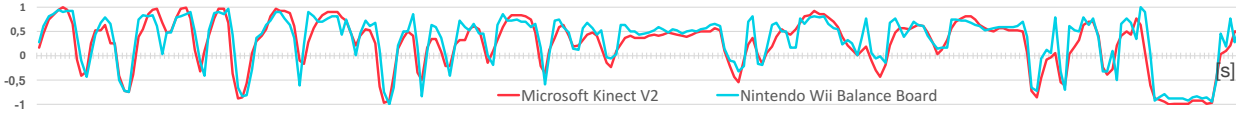


Figure 5.22: Normalized *CoP* oscillation acquired both with Microsoft Kinect V2 and Wii Balance Board during a comparison test. Time is on the *x*-axis (2-min-long trial).

performances in the serious games context; in fact, according to the studies we have carried out, the Microsoft Kinect V2 can be exploited for the estimation of the oscillation of the *CoP* on the mediolateral axis and WBB would be redundant and anti-economic. The following procedure will disclose the method for the *CoP* estimation using the Microsoft Kinect V2:

- Track the position in space of these fundamental body joints provided by Kinect SDK: right ankle (A_r), left ankle (A_l), the base of the spine (S_{bottom}), and the spine at the shoulder height (S_{top}) (Figure 5.20a).
- Compute the position in space of the middle point (M) between the right ankle and the left ankle.
- Compute the difference between the angles related to the shift of lower and higher sections of the trunk:

$$\begin{aligned} Tilt_{bottom} &= \angle(A_r, M, S_{bottom}) - \angle(A_l, M, S_{bottom}), \\ Tilt_{top} &= \angle(A_r, M, S_{top}) - \angle(A_l, M, S_{top}). \end{aligned} \quad (5.10)$$

- Calculate the average between the $Tilt_{bottom}$ and $Tilt_{top}$ to get the estimated *CoP*:

$$CoP = \frac{Tilt_{bottom} + Tilt_{top}}{2}. \quad (5.11)$$

We used this experimental setup to evaluate the performance of the proposed algorithm: three subjects repeated a 2-min-long serious game for postural assessment ten times. Data were synchronously recorded from WBB and Microsoft Kinect V2 and the *CoP* oscillation on the mediolateral were normalized and compared calculating the Pearson correlation coefficient. The average of the coefficients calculated for each test sessions brought the result of ~ 0.89 . Figure 5.22 shows a sample of synchronized and normalized data in a 2-min-long test session.

Balance Control

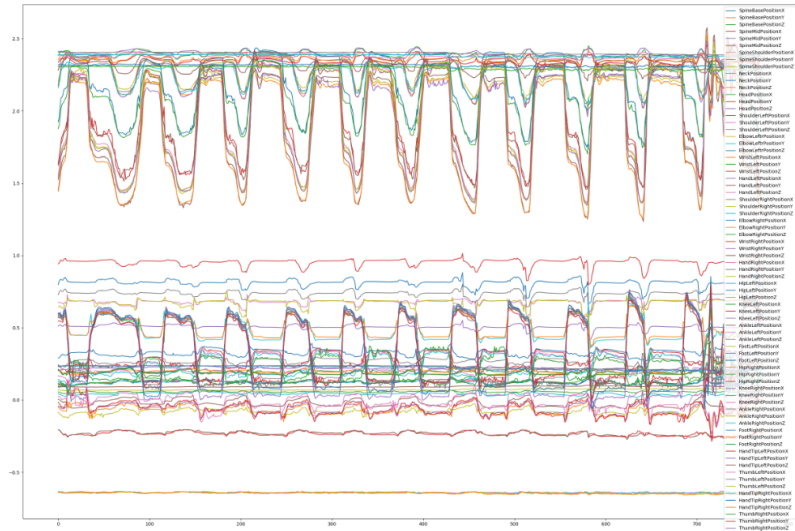
The exergame Push Box takes its cue from one of the tests in Berg's Balance Test. The patient must extend his arms forward keeping a suitable potion and controlling his balance. It is therefore important to analyze the movement phases and extract some indicators, which are:

- ▶ **Time Phase 0:** the number of frames (each one captured every 0.1 seconds) in which, inside of the segment, the player stays in the phase 0 of PushBox (Figure 3.13). A larger number of this feature points out the difficulty to reach the validity position.
- ▶ **Time Phase 1:** the number of frames in which, inside of the segment, the player stays in the phase 1 of PushBox. A larger number of this feature points out the difficulty to reach the 85% of the maximum range of motion vested in the calibration phase.
- ▶ **Range Of Motion:** the maximum distance between feet and hands inside the analyzed segment (for better accuracy ankles and wrists are then used instead of feet and hands). If this value is closer to the maximum range of motion reached up in the calibration phase it is a indicator of good performance.
- ▶ **Compensation:** computes the average knee angle (i.e. the angle among ankle, knee and hip) expressed in degrees between frames of the analyzed segment. The excellent execution of the PushBox exercise expected to do not bend the knees, so the knee angle should be approximately 180°; a smaller value denotes a worse quality of exercise.
- ▶ **1 to 0 phase:** number of times in which, inside of the segment, there was a transition from phase 1 to phase 0 of PushBox. This fact indicates problem to keep the validity position, for some reason.
- ▶ **1 to 2 phase:** number of times in which, inside of the segment, there was a transition from phase 1 to phase 2 of PushBox. If this feature have value 1 or more means that it has been reached the 85% of the ROM, so it is an indicator of good execution of the exercise; on the other hand a 0 value of this feature does not necessarily indicate a bad execution (because, for example, the player could be in other phases of the game).

To get an idea of the quality of data obtained, we have

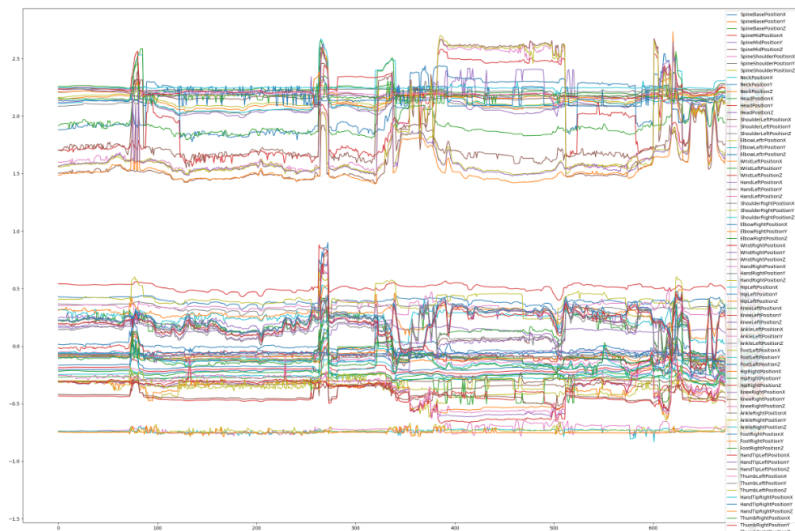
extracted all the 25 joints positions (x, y, z) detected from the Kinect V2 frame by frame. An example of graph of healthy player is in Figure 5.23: it shows a periodic trend due to the repetition of the movements required by the exergame. We also note that some joints are not indicative to our study because their variation is quite small.

Figure 5.23: All the 25 joints positions of a healthy player detected from the Kinect V2 frame by frame.



On the contrary in Figure 5.24 and in Figure 5.25 we can see two graphs of players with diseases: in one case the periodic and clean progress of the previous image there is no more and in the second graph the positions are noisy.

Figure 5.24: Graph of impaired player: the periodic trend is no longer noticed.



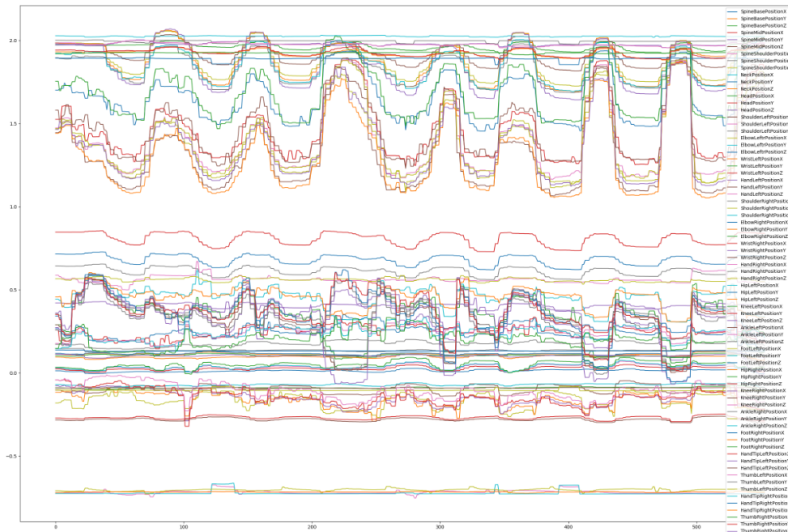


Figure 5.25: Graph of impaired player: noisy and confusing data.

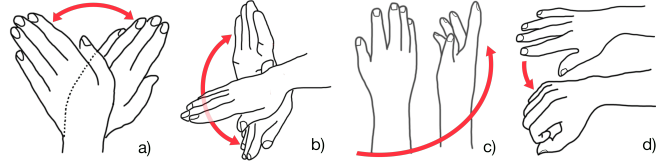
Hand Movements

Leap Motion was deployed in this analysis: the digital games encourage the patient to control in-game objects with hand, wrist, and finger motion. The main movements tracked during the execution of functional exercises are: Radial–Ulnar deviation (Figure 5.26a), Flexion–Extension (Figure 5.26b), Pronation–Supination (Figure 5.26c), and Grasping (Figure 5.26d).

From the motion data, we extract these fundamental features:

- **Repetition rate:** same as previous activities.
- **Maximum angle:** maximum angle reached in each of the proposed movement (corresponding to yaw, pitch, and roll). These values are tracked, respectively, in *EndlessZig*, *CityCar*, and *WineBottle* games.
- **Grab strength:** evaluation of the grasping exercise with Grab strength function provided by Leap Motion SDK that returns values between 0 and 1 respectively when the hand is open or when it is closed in a grabbing pose. This feature is currently tracked in the **FloatingTrap** serious game.

Figure 5.26: Movements detected during hand rehabilitation with Leap Motion: (a) Radial–Ulnar deviation movement in EndlessZig game; (b) Flexion–Extension movement in CityCar game; (c) Pronation–Supination movement in WineBottle game; (d) Grasping movement in FloatingTrap game.



Cognitive

This section is under development: final studies are currently underway.

5.4 Method 2: SVM Classification

This section presents the results of the application of the SVM classification method, described in Section 4.2. We recall that the method is based on the optimization of the hyper-parameter t , which subdivides each game session (typically of 120 seconds) into segments of shorter duration (Fig. 5.27). This procedure provides more granularity and a larger dataset, and the choice of t must be made accurately for each exergame. The method is applied to two of the exergames in the ReMoVES catalog: Push Box (balance control) and Shelf Cans (upper limbs). The accuracy of the classification model is provided for each activity.

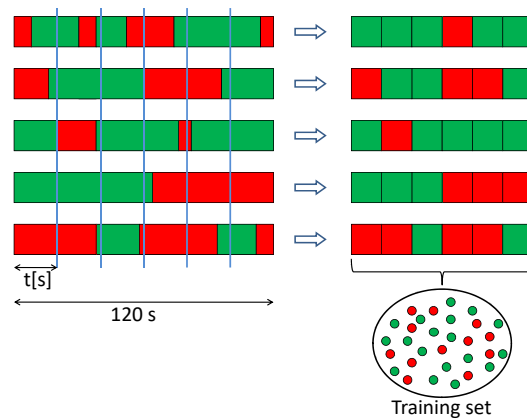


Figure 5.27: Example of splitting game sessions corresponding to t and the resulting training set.

Push Box

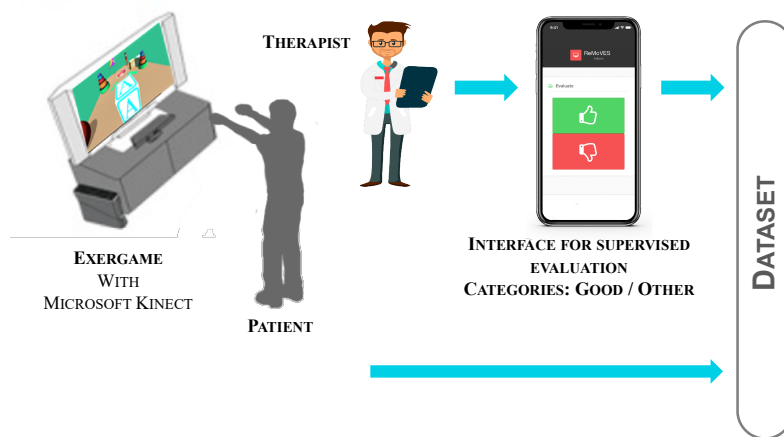


Figure 5.28: General scheme for construction of the dataset: therapist watches patient playing with PushBox exergame and through the web interface evaluates the patient's performance.

During the execution of the activity by the patient, the therapist has classified 17 sessions of Push Box exergames, for a total of 34 minutes. During each session, the patient's performance can be unsteady, for instance:

- ▶ the patient starts with poor performance because he must become familiar with the game (Fig. 5.29, red zone with label 1);
- ▶ the patient plays correctly for a good part of the session (Fig. 5.29, green zone);
- ▶ the patient makes an error during the session (Fig. 5.29, red zone with label 2);
- ▶ the patient perceives fatigue, and the performance decreases towards the end of the activity (Fig. 5.29, red zone with label 3).

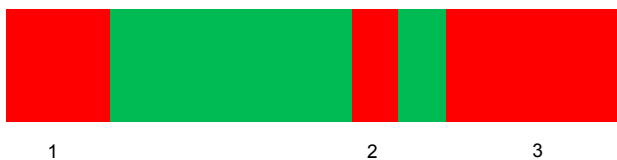


Figure 5.29: The green zones indicate good performance and are labeled as "Good", while the red ones are labeled as "Other".

An entire game session is sampled at the frequency of 10Hz; if one session has a duration of 120 seconds, we obtained 1200 samples, which translate into 1200 rows of the JSON log file. A row is composed of these fields:

- ▶ Timestamp (millisecond timestamp)

- ▶ Evaluation (1 for “Good”, 2 for “Other”, 0 for missing evaluation)
- ▶ Score (in-game score)
- ▶ CountRepetition (how many boxes were thrown into the hole)
- ▶ PushBox_Phase (0, 1, 2 or 3)
- ▶ Joint_1 [x,y,z]
- ▶ Joint_2 [x,y,z]
- ▶ ...

Using the SessionID as an identifier to distinguish sessions, all rows (corresponding to a timestamp) are stored in a unified DataRowList matrix. With 17 sessions and 1200 samples each, the matrix has 20400 rows. Approximately 50% entries are rated as “Good” and 50% rated as “Other” so as having a balanced dataset.

BEGIN: Iterate the segment size t

The following operations are to be repeated for each t :

$$t \in \{2.0, 2.1, \dots, 20.0\} \quad [s]$$

Once obtained the DataRowList, it must be used to generate segments of duration t , obviously discarding the rest of the division if the length of a session (120s) is not divisible by the current t . In this case, it was decided to drop the last samples of each session as they are less significant and sometimes not classified by the therapist.

For each segment, the features are calculated based on the indicators presented in Section 5.3: most of them are related to the patient’s movements and use the tracking provided by Microsoft Kinect.

Table 5.5: Push Box dataset structure: Session#ID and Segment#N are provided just for identification purpose; Evaluation defines the two target classes (Y); others are the features (X).

Name	Type	Role	Description
Session#ID	numeric	meta	for identification purposes only
Segment#N	numeric	meta	for identification purposes only
Evaluation	categorical	label	“Good”, “Other”
Time Phase 0	numeric	feature 1	
Time Phase 1	numeric	feature 2	
Range of Motion	numeric	feature 3	
Compensation	numeric	feature 4	
1 to 0 phase	numeric	feature 5	
1 to 2 phase	numeric	feature 6	

The supervised classification takes place using the X vector of the features (input variables) and the Y vector with targets

“Good” or “Other” (output variable), where each sample is made up of a segment (Table 5.5). In Figure 5.30, a summary of the phases performed starting from the DataRawList matrix up to the definition of the dataset relating to the current t is shown.

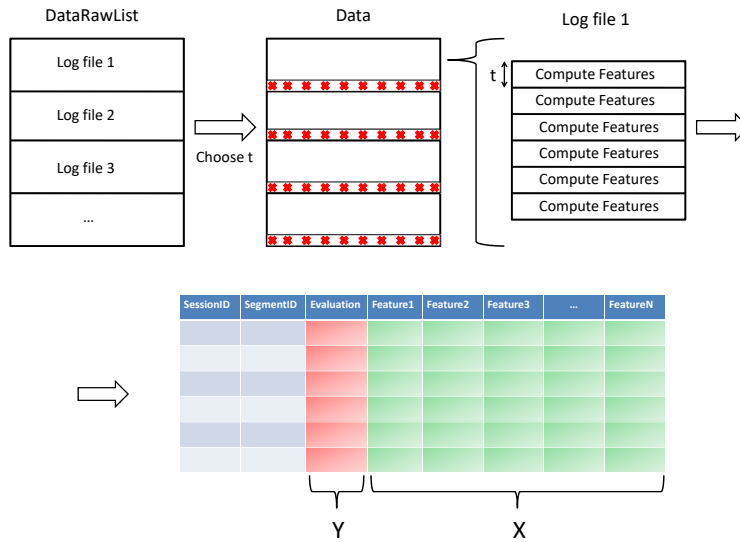


Figure 5.30: Steps from DataRawList to the definition of the dataset. Y represents the output vector, X the feature matrix (input). Y and X will be used by the SVM learning process.

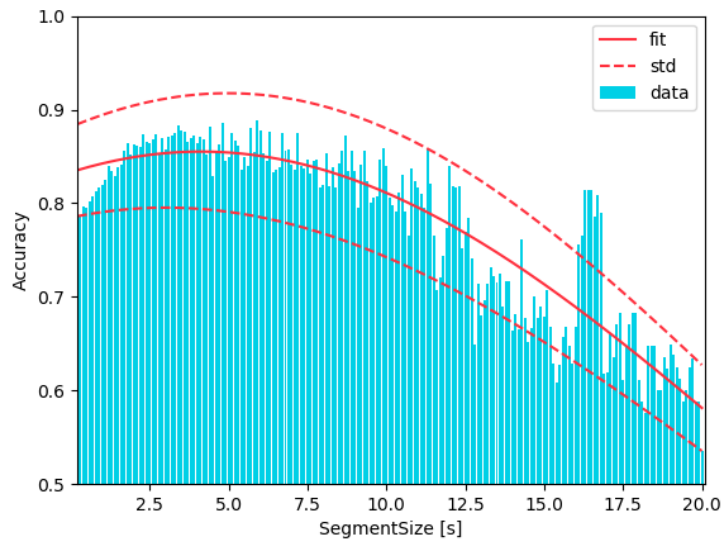
This dataset is employed by the SVM learning process. The performance of the model is evaluated through 5-fold cross-validation. The resulting accuracy relative to the current t is the average of the accuracy of each fold of the cross-validation.

END: Iterate the segment size t

The relation $accuracy = f(t)$ is defined using all the accuracy calculated during the iteration for each t

We used non-linear least squares to fit the accuracy data and understand whether it presented a global maximum. The outcomes are in Figure 5.31. It can be noted that the maximum is when $t = 5.9$ and this has been selected as final t of the “grid search” process. A peak is found around $t = 17$: the explanation of this unexpected behavior can be caused by the fact that with long segment sizes the dataset is composed of few values causing overfitting problems. It is advisable to ignore strange results with high t values.

Figure 5.31: Push Box exergame-Plot of accuracy for each iteration of the “grid search” process for t between 2.0 (extended to 0.5) and 20.0 seconds with 0.1 steps. The curve (in red) that fits the data has the global maximum in $t = 5.9$.



Once it is established that the best segment time for the accuracy is 5.9 seconds, the model related to this segment size is trained. In this configuration the dataset consists of:

- ▶ 286 samples
- ▶ 154 samples labeled as “Good”
- ▶ 132 samples labeled as “Other”

1: Orange is an open-source data visualization, machine learning, and data mining toolkit. It is a GUI-based tool for explorative data analysis and interactive data visualization.

To better visualize the dataset, we perform a Principal Component Analysis (PCA) with Orange¹ and plot the result with two principal features (Figure 5.32).

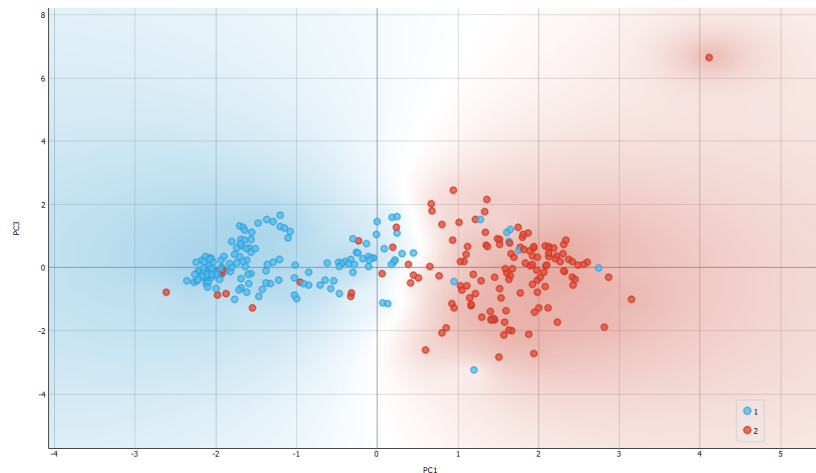


Figure 5.32: Principal Component Analysis (PCA) of two components (PC1, PC3) applied to dataset obtained with segment size $t = 5.9$ seconds.

From the graphic representation, the PCA allows identifying two distinct classification areas between the left samples labeled with “Good” (blue) and those on the right marked with “Other” (red).

The final confusion matrix for $t = 5.9$ is provided in Table 5.6.

		Predicted		Total
		Good	Other	
Actual	Good	146	8	154
	Other	15	117	132
Total		161	125	286

Table 5.6: Push Box exergame: SVM performance expressed as a confusion matrix. The hyperparameter is $t = 5.9$ based on the optimization of the “grid search”.

The accuracy score is calculated from the confusion matrix, and it is defined as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100$$

where TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

The resulting accuracy of the SVM model for Push Box exergame, with the optimized $t = 5.9$ is $Accuracy = 0.919$.

Other parameters are:

- AUC (Area under the receiver-operating curve) of 0.948. Over 0.9 is considered excellent;
- Precision (proportion of true positives among instances classified as positive) of 0.917;
- Recall (ratio of true positives among all positive samples in the data) of 0.916;
- F1 (weighted harmonic mean of precision and recall) of 0.916.

Shelf Cans

The Shelf Cans exergame was treated in the same way as the Push Box, described in the previous section. Only the differences in the dataset and the performances are therefore highlighted.

The classified data related to the Shelf Can exergame at our disposal are 30 sessions of 120 seconds each. Motion data is acquired by Microsoft Kinect at frequency of 10Hz. Each session is divided into segments according to the duration expressed by the hyperparameter t , ensuring hundreds of samples for the dataset. The two classes “Good” and “Other”

Table 5.7: Shelf Cans dataset structure: Session#ID and Segment#N are provided just for identification purpose; Evaluation defines the two target classes (Y); others are the features (X).

Name	Type	Role	Description
Session #ID	numeric	meta	for identification purposes only
Segment #N	numeric	meta	for identification purposes only
Evaluation	categorical	label	“Good”, “Other”
Score	numeric	feature 1	
Trajectory	numeric	feature 2	
Compensation	numeric	feature 3	
Barycenter	numeric	feature 4	
Range of Motion	numeric	feature 5	
Tilt	numeric	feature 6	
Twist	numeric	feature 7	

are balanced. Each sample in the database is composed as summarized in Tab. 5.7.

The “grid search” for the hyperparameter t is performed by training the corresponding models and evaluating their performance by iterating the 5-fold cross-validation for t between 2.0 and 20.0 seconds with 0.1 steps.

The Fig. 5.33 shows the outcome: the fitted curve has a maximum in $t = 8.3$ seconds, therefore this is the result of the “grid search”. The t parameter, as already explained, indicates the duration of the segments in which each session must be divided: the value $t = 8.3$ automatically selected by the method is a reasonable value for this Shelf Cans activity, in relation to the typical duration of a complete cycle movement carried out by a patient.

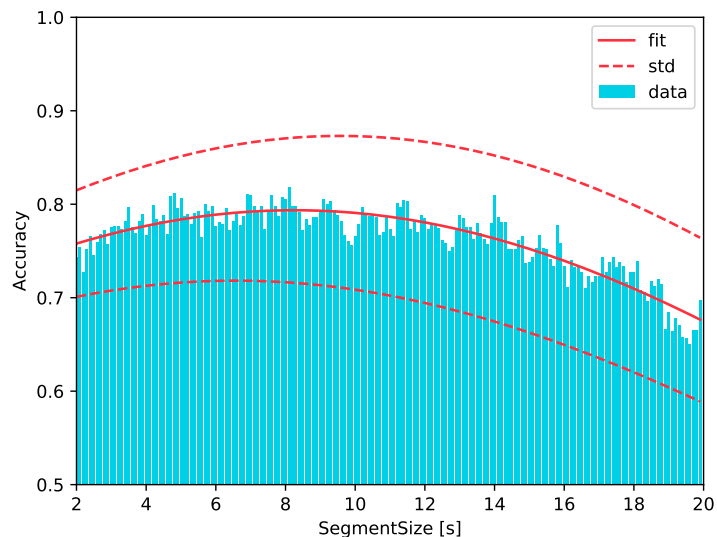


Figure 5.33: Shelf Cans exergame. Plot of accuracy for each iteration of the “grid search” process for t between 2.0 and 20.0 seconds with 0.1 steps. The curve (in red) that fits the data has the global maximum in $t = 8.3$.

Once it is established that the best segment time for the accuracy is 8.3 seconds, the model related to this segment size is trained. In this configuration the dataset consists of:

- 389 samples
- 200 samples labeled as “Good”
- 189 samples labeled as “Other”

The final confusion matrix is provided in Table 5.8.

Actual	Predicted		Total
	Good	Other	
Good	128	72	200
Other	7	182	189
Total	135	254	389

Table 5.8: Shelf Cans exergame: SVM performance expressed as a confusion matrix. . The hyperparameter is $t = 8.3$ based on the optimization of the “grid search”.

The resulting accuracy of the SVM model for Push Box exergame, with the optimized $t = 8.3$ is $Accuracy = 0.796$.

5.5 Method 3: LSTM Classification

Equilibrium Paint

In order to provide an automatic evaluation of game sessions, a Long-Short Time Memory Recurrent Neural Network (LSTM RNN [95]) to analyze the raw data collected by the system has been developed and tested. In addition to the previously considered patients, the game sessions from healthy subjects (subjects 25, 26, 40, 59, 71, 106, 107, 108) and from other impaired patients (patients 35 and 38) have been included in the used dataset. Figure 5.34 shows the number of sit-ups in 30 seconds along the performed sessions related to the patients and subjects who attended the exergame several times.

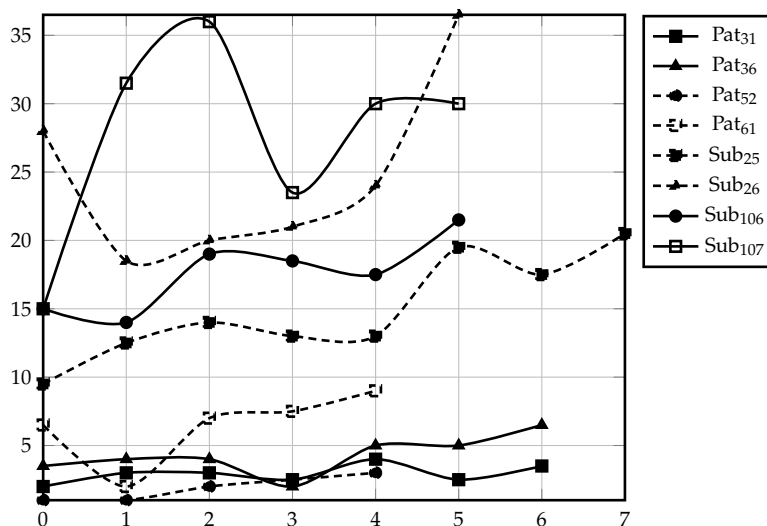


Figure 5.34: Sit-ups trend along the several game sessions.

In this preliminary study, patients 35, 36, 38, 52, 61 and subjects 25, 26, 40, 59, 71, 107, 108 constitute the cross-validated training set, while subjects 31 and 106 are included in the test set. To sum up, 50 sessions for training and 13 for testing have been used. Each game sessions is split into 5 segments in order to augment the dataset. Finally, the training set consists of 250 samples and the test set consisted of 65 samples. Table 5.9 shows the confusion matrix related to this study. The obtained overall accuracy is 92.31%.

Table 5.9: Confusion matrix and accuracy metrics values for the classification.

		Predicted		Total
		Good	Other	
Actual	Good	30	5	35
	Other	0	30	30
Accuracy		100%	85.71%	92.31%

These results are a simple demonstration of the applicability of an RNN-based method for performance classification during the execution of an STS exercise. Further evaluation and validation are necessary when a larger and more homogeneous dataset (e.g. age between the two classes) will be accessible.

The ReMoVES platform is devoted to administer exergames for motor and cognitive activities to elderly and disabled subjects according to their personalized plan of care. By using low-cost off-the-shelf components and an easy-to-use interface, the patient activity can be monitored even when executed without expert supervision. Self-sufficient elderly as well as de-hospitalized patients might benefit from this system to reduce sedentary attitudes, for the preservation of motor and cognitive abilities and the maintenance of rehabilitation results.

Discussion: database release

A database released for the purpose of scientific research has been described. The preliminary outcomes suggested to elaborate reports on the learning rate when the same exergames are repeated, to compare movements of the right and left arms in task-oriented exercises, to search for correlation between sessions performance indicators and standard medical indices, and to leverage on machine learning algorithms to provide an automatic and remote evaluation about the quality of patient's activities. However, since the most important scope of this work is to encourage the scientific community to the development of assistive computing technologies, the publicly released database is meant to be used in order to provide many different contribution to this field.

Discussion: SVM performance

This study demonstrates the reliability of ReMoVES as a support tool for rehabilitation and the machine learning method based on "Support Vector Machine" provides a solid system of automatic assessment of patient performance. Therefore, ReMoVES can be used as a training tool through exergame even when the user is not supervised directly by the therapist. In the Push Box activity, the accuracy of the movement quality classification process is 0.919. In the Shelf

Cans activity the performances are equal to 0.796: although not exciting, they are nevertheless consistent with the results described in [81], although a direct correlation is challenging due to the lack of raw comparison and benchmark data.

Discussion: LSTM performance

The application of LSTM neural networks for the evaluation of time series of rehabilitation movement data through exergames is an innovative factor. The method was applied only to the Equilibrium Paint activity to study its feasibility. The results are promising, offering a classification accuracy of 0.923. It is appropriate to acquire more data and investigate the possibility of applying this method to the other ReMoVES' exergames for motor rehabilitation. This method uses raw motion data without the need to manually define and select features, thus allowing a comprehensive analysis with less human intervention.

Conference Papers

- ▶ Graph-Based Region Competition for Automatic Image Segmentation [*unpublished*]
- ▶ M. Morando, M. Trombini, and S. Dellepiane. "Application of SVM for Evaluation of Training Performance in Exergames for Motion Rehabilitation" in: *Proceedings of the 2019 International Conference on Intelligent Medicine and Image Processing*. ACM. 2019, pp. 1–5.
<https://doi.org/10.1145/3332340.3332342>
- ▶ M. Morando, E. B. Bonotti, G. Giannarelli, S. Olivieri, S. Dellepiane, and F. Cecchi, "Monitoring Home-Based Activity of Stroke Patients: A Digital Solution for Visuo-Spatial Neglect Evaluation" in: *Converging Clinical and Engineering Research on Neurorehabilitation III ICNR 2018*. Biosystems & Biorobotics, vol 21. Springer, Cham.
https://doi.org/10.1007/978-3-030-01845-0_139
- ▶ M. Morando, S. Ponte, E. Ferrara, and S. Dellepiane, "Biophysical and Motion Features Extraction for an effective home-based Rehabilitation" in *ICBRA 2017: Proceedings of the International Conference on Bioinformatics Research and Applications 2017*, pp. 79–85.
<https://doi.org/10.1145/3175587.3175597>
- ▶ S. Ponte, S. Gabrielli, J. Jonsdottir, M. Morando, and S. Dellepiane, "Monitoring game-based motor rehabilitation of patients at home for better plans of care and quality of life" in *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Milan, 2015*, pp. 3941–3944.
<https://doi.org/10.1109/EMBC.2015.7319256>

Journals

- ▶ Motion and Cognitive Rehabilitation through Exergames: a Dataset for Automatic Evaluation [*unpublished*]
- ▶ M. Morando, S. Ponte, E. Ferrara, and S. Dellepiane, "Definition of motion and biophysical indicators for home-based rehabilitation through serious games." in

Information 9.5 (2018): 105.

<https://doi.org/10.3390/info9050105>

Chapter in book

- E. Ferrara, S. Ponte, M. Morando, and S. Dellepiane, "ReMoVES Remote Monitoring Validation Engineering System: New Way of Care" in N. Casiddu, et al., eds. *Ambient Assisted Living: Italian Forum 2017 (Vol. 540)*. Springer 2019. <https://www.springer.com/it/book/9783030046712>

Presenting at Conferences and Workshops

- M. Morando, M. Trombini, and S. Dellepiane, "Remote Evaluation of Rehabilitative Activity and Disability Assessment via Exergames." in *Workshop "Innovation in Rehabilitation Technologies, Genova, 2019*
- S. Dellepiane, M. Morando, and G. Regesta, "Exergames e tecnologie ICT nella riabilitazione neuromotoria e cognitiva.", in *XVIII Congresso Nazionale della Società Italiana per lo Studio dello Stroke, Napoli, 2018*.
- S. Ponte, M. Morando, E. Ferrara, and M. Simonini, "Validazione del sistema ReMoVES per il Monitoraggio Remoto della riabilitazione" in *45° Congresso Nazionale SIMFER, Riabilitazione e disabilità attraverso il ciclo della vita, Genova, 2017*
- E. Ferrara, S. Ponte, M. Morando, and S. Dellepiane "ReMoVES Remote Monitoring Validation Engineering System: new way of care" in *Forum Italiano Ambient Assisted Living, Genova, 2017 ForITAAL2017*.
- S. Ponte, M. Morando, E. Ferrara, S. Dellepiane, and G. Regesta, "Riabilitazione e monitoraggio della terapia post-stroke a casa: la piattaforma ReMoVES", in *XVII Congresso Nazionale della Società Italiana per lo Studio dello Stroke, Bologna, 2017*.

scientific acknowledgments and Awards

- The ReMoVES project participated in the Start Cup 2016 contest organized by the Università degli Studi di Genova for innovative startups, winning the third prize.

Bibliography

Here are the references in citation order.

- [1] Exergame. *Macmillan English Dictionary for Advanced Learners*. Macmillan Education, 2019 (cited on page 1).
- [2] Emma Stanmore et al. 'The effect of active video games on cognitive functioning in clinical and non-clinical populations: a meta-analysis of randomized controlled trials'. In: *Neuroscience & Biobehavioral Reviews* 78 (2017), pp. 34–43 (cited on pages 1, 9).
- [3] Krista L Lanctôt et al. 'Canadian Stroke Best Practice Recommendations: Mood, Cognition and Fatigue following Stroke, update 2019'. In: *International Journal of Stroke* (2019), p. 1747493019847334 (cited on page 1).
- [4] Serena Ponte et al. 'Monitoring game-based motor rehabilitation of patients at home for better plans of care and quality of life'. In: *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*. IEEE. 2015, pp. 3941–3944 (cited on page 2).
- [5] Jan-Henk Annema et al. 'Videogames in therapy: a therapist's perspective'. In: *Proceedings of the 3rd International Conference on Fun and Games*. ACM. 2010, pp. 94–98 (cited on page 5).
- [6] Aurelio Cappozzo et al. 'Position and orientation in space of bones during movement: anatomical frame definition and determination'. In: *Clinical biomechanics* 10.4 (1995), pp. 171–178 (cited on page 5).
- [7] C Frigo et al. 'Functionally oriented and clinically feasible quantitative gait analysis method'. In: *Medical and Biological Engineering and Computing* 36.2 (1998), pp. 179–185 (cited on page 5).
- [8] Aurelio Cappozzo et al. 'Position and orientation in space of bones during movement: experimental artefacts'. In: *Clinical biomechanics* 11.2 (1996), pp. 90–100 (cited on page 5).
- [9] J Fuller et al. 'A comparison of lower-extremity skeletal kinematics measured using skin-and pin-mounted markers'. In: *Human movement science* 16.2-3 (1997), pp. 219–242 (cited on page 5).
- [10] Stefano Corazza et al. 'A markerless motion capture system to study musculoskeletal biomechanics: Visual hull and simulated annealing approach'. In: *Annals of biomedical engineering* 34.6 (2006), pp. 1019–1029 (cited on page 5).
- [11] Ugo Della Croce et al. 'Human movement analysis using stereophotogrammetry: Part 4: assessment of anatomical landmark misplacement and its effects on joint kinematics'. In: *Gait & posture* 21.2 (2005), pp. 226–237 (cited on page 5).

- [12] Lorenzo Chiari et al. 'Human movement analysis using stereophotogrammetry: Part 2: Instrumental errors'. In: *Gait & posture* 21.2 (2005), pp. 197–211 (cited on page 5).
- [13] Zhengyou Zhang. 'Microsoft kinect sensor and its effect'. In: *IEEE multimedia* 19.2 (2012), pp. 4–10 (cited on page 6).
- [14] Elise Klaebo Vonstad et al. 'Classification of Movement Quality in A Weight-shifting Exercise.' In: *KHD@ IJCAI*. 2018, pp. 27–32 (cited on page 6).
- [15] Belinda Lange et al. 'Development and evaluation of low cost game-based balance rehabilitation tool using the Microsoft Kinect sensor'. In: *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE. 2011, pp. 1831–1834 (cited on page 7).
- [16] Kirk Woolford. 'Defining accuracy in the use of Kinect v2 for exercise monitoring'. In: *Proceedings of the 2nd International Workshop on Movement and Computing*. ACM. 2015, pp. 112–119 (cited on page 7).
- [17] Silvio Giancola et al. 'Motion capture: an evaluation of kinect V2 body tracking for upper limb motion analysis'. In: *International Conference on Wireless Mobile Communication and Healthcare*. Springer. 2016, pp. 302–309 (cited on page 7).
- [18] Adyasha Dash et al. 'Kinect-assisted performance-sensitive upper limb exercise platform for post-stroke survivors'. In: *Frontiers in Neuroscience* 13 (2019), p. 228 (cited on page 7).
- [19] Wan-wen Liao, Sandy McCombe Waller, and Jill Whitall. 'Kinect-based individualized upper extremity rehabilitation is effective and feasible for individuals with stroke using a transition from clinic to home protocol'. In: *Cogent Medicine* 5.1 (2018). Ed. by Udo Schumacher, p. 1428038. doi: [10.1080/2331205X.2018.1428038](https://doi.org/10.1080/2331205X.2018.1428038) (cited on page 7).
- [20] Brook Galna et al. 'Retraining function in people with Parkinson's disease using the Microsoft kinect: game design and pilot testing'. In: *Journal of neuroengineering and rehabilitation* 11.1 (2014), p. 60 (cited on page 7).
- [21] Jorge Cancela, Maria T Arredondo, and Olivia Hurtado. 'Proposal of a Kinect TM-based system for gait assessment and rehabilitation in Parkinson's disease'. In: *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE. 2014, pp. 4519–4522 (cited on page 7).
- [22] Naofumi Kitsunezaki et al. 'KINECT applications for the physical rehabilitation'. In: *2013 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*. IEEE. 2013, pp. 294–299 (cited on page 7).
- [23] Jaime Andres Garcia et al. 'Exergames for the elderly: Towards an embedded Kinect-based clinical test of falls risk.' In: *HIC*. 2012, pp. 51–57 (cited on page 7).
- [24] Lisbeth H Larsen et al. 'The physical effect of exergames in healthy elderly—a systematic review'. In: *GAMES FOR HEALTH: Research, Development, and Clinical Applications* 2.4 (2013), pp. 205–212 (cited on page 7).

- [25] Mike van Diest et al. 'Suitability of Kinect for measuring whole body movement patterns during exergaming'. In: *Journal of biomechanics* 47.12 (2014), pp. 2925–2932 (cited on page 7).
- [26] Qifei Wang et al. 'Evaluation of pose tracking accuracy in the first and second generations of microsoft kinect'. In: *2015 international conference on healthcare informatics*. IEEE. 2015, pp. 380–389 (cited on page 7).
- [27] Jože Guna et al. 'An analysis of the precision and reliability of the leap motion sensor and its suitability for static and dynamic tracking'. In: *Sensors* 14.2 (2014), pp. 3702–3720 (cited on page 7).
- [28] D Bassily et al. 'Intuitive and adaptive robotic arm manipulation using the leap motion controller'. In: *ISR/robotik 2014; 41st international symposium on robotics; proceedings of VDE*. 2014, pp. 1–7 (cited on pages 8, 19).
- [29] Igor Zubrycki and Grzegorz Granosik. 'Using integrated vision systems: three gears and leap motion, to control a 3-finger dexterous gripper'. In: *Recent advances in automation, robotics and measuring techniques*. Springer, 2014, pp. 553–564 (cited on page 8).
- [30] Maryam Khademi et al. 'Free-hand interaction with leap motion controller for stroke rehabilitation'. In: *CHI'14 Extended Abstracts on Human Factors in Computing Systems*. ACM. 2014, pp. 1663–1668 (cited on pages 8, 19).
- [31] Wen-Jeng Li et al. 'Hand gesture recognition for post-stroke rehabilitation using leap motion'. In: *2017 International Conference on Applied System Innovation (ICASI)*. IEEE. 2017, pp. 386–388 (cited on page 8).
- [32] Marco Iosa et al. 'Leap motion controlled videogame-based therapy for rehabilitation of elderly patients with subacute stroke: a feasibility pilot study'. In: *Topics in stroke rehabilitation* 22.4 (2015), pp. 306–316 (cited on page 8).
- [33] Ela Tarakci et al. 'Leap Motion Controller-based training for upper extremity rehabilitation in children and adolescents with physical disabilities: A randomized controlled trial'. In: *Journal of Hand Therapy* (2019) (cited on page 8).
- [34] Gaoxia Zhu et al. 'A series of leap motion-based matching games for enhancing the fine motor skills of children with autism'. In: *2015 IEEE 15th International Conference on Advanced Learning Technologies*. IEEE. 2015, pp. 430–431 (cited on page 8).
- [35] Paulo Bazile da Silva et al. 'Strength training associated with task-oriented training to enhance upper-limb motor function in elderly patients with mild impairment after stroke: a randomized controlled trial'. In: *American journal of physical medicine & rehabilitation* 94.1 (2015), pp. 11–19 (cited on page 8).
- [36] Hyun-Gyu Cha and Duck-Won Oh. 'Effects of mirror therapy integrated with task-oriented exercise on the balance function of patients with poststroke hemiparesis: a randomized-controlled pilot trial'. In: *International Journal of Rehabilitation Research* 39.1 (2016), pp. 70–76 (cited on page 8).
- [37] Joaquin A Anguera et al. 'Video game training enhances cognitive control in older adults'. In: *Nature* 501.7465 (2013), p. 97 (cited on page 8).

- [38] Kirk I Erickson et al. 'Exercise training increases size of hippocampus and improves memory'. In: *Proceedings of the National Academy of Sciences* 108.7 (2011), pp. 3017–3022 (cited on page 9).
- [39] Shoshanna Vaynman, Zhe Ying, and Fernando Gomez-Pinilla. 'Hippocampal BDNF mediates the efficacy of exercise on synaptic plasticity and cognition'. In: *European Journal of Neuroscience* 20.10 (2004), pp. 2580–2590 (cited on page 9).
- [40] Kathrin Maria Gerling, Jonas Schild, and Maic Masuch. 'Exergame design for elderly users: the case study of SilverBalance'. In: *Proceedings of the 7th International Conference on Advances in Computer Entertainment Technology*. ACM. 2010, pp. 66–69 (cited on page 9).
- [41] WA Wallace and RE Coupland. 'Variations in the nerves of the thumb and index finger'. In: *The Journal of bone and joint surgery. British volume* 57.4 (1975), pp. 491–494 (cited on page 9).
- [42] Scott H Johnson. 'Cerebral organization of motor imagery: contralateral control of grip selection in mentally represented prehension'. In: *Psychological Science* 9.3 (1998), pp. 219–222 (cited on page 10).
- [43] Hana Skala Kavanagh et al. 'Computer supported thermography monitoring of hand strength evaluation by electronic dynamometer in rheumatoid arthritis—a pilot study'. In: *Periodicum biologorum* 113.4 (2011), pp. 433–437 (cited on page 10).
- [44] Sofia Olandersson et al. 'Finger-force measurement-device for hand rehabilitation'. In: *9th International Conference on Rehabilitation Robotics, 2005. ICORR 2005*. IEEE. 2005, pp. 135–138 (cited on page 10).
- [45] Sergiu Hartopanu et al. 'Design of a hybrid FES-mechanical intelligent haptic robotic glove'. In: *2013 17th International Conference on System Theory, Control and Computing (ICSTCC)*. IEEE. 2013, pp. 687–692 (cited on page 10).
- [46] Elizabeth B Brokaw et al. 'Hand Spring Operated Movement Enhancer (HandSOME): a portable, passive hand exoskeleton for stroke rehabilitation'. In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 19.4 (2011), pp. 391–399 (cited on page 10).
- [47] Jiting Li et al. 'Development of a hand exoskeleton system for index finger rehabilitation'. In: *Chinese journal of mechanical engineering* 25.2 (2012), pp. 223–233 (cited on page 10).
- [48] Andreas Wege and Günter Hommel. 'Development and control of a hand exoskeleton for rehabilitation of hand injuries'. In: *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE. 2005, pp. 3046–3051 (cited on page 10).
- [49] Christina Gummesson, Isam Atroshi, and Charlotte Ekdahl. 'The disabilities of the arm, shoulder and hand (DASH) outcome questionnaire: longitudinal construct validity and measuring self-rated health change after surgery'. In: *BMC musculoskeletal disorders* 4.1 (2003), p. 11 (cited on page 10).
- [50] Richard W Bohannon. 'Sit-to-stand test for measuring performance of lower extremity muscles'. In: *Perceptual and motor skills* 80.1 (1995), pp. 163–166 (cited on page 10).

- [51] Pao-Tsai Cheng et al. 'The sit-to-stand movement in stroke patients and its correlation with falling'. In: *Archives of physical medicine and rehabilitation* 79.9 (1998), pp. 1043–1046 (cited on page 10).
- [52] Juliet Rosie and Denise Taylor. 'Sit-to-stand as home exercise for mobility-limited adults over 80 years of age—GrandStand System TM may keep you standing?' In: *Age and ageing* 36.5 (2007), pp. 555–562 (cited on page 10).
- [53] Angie Logan et al. 'Standing Practice In Rehabilitation Early after Stroke (SPIRES): a functional standing frame programme (prolonged standing and repeated sit to stand) to improve function and quality of life and reduce neuromuscular impairment in people with severe sub-acute stroke—a protocol for a feasibility randomised controlled trial'. In: *Pilot and feasibility studies* 4.1 (2018), p. 66 (cited on page 10).
- [54] Richard W Bohannon. 'Daily sit-to-stands performed by adults: a systematic review'. In: *Journal of physical therapy science* 27.3 (2015), pp. 939–942 (cited on page 10).
- [55] Susan Barreca et al. 'Effects of extra training on the ability of stroke survivors to perform an independent sit-to-stand: a randomized controlled trial'. In: *Journal of Geriatric Physical Therapy* 27.2 (2004), p. 59 (cited on page 10).
- [56] Andre de Souza Rocha, Rodrigo José Knabben, and Stella Maris Michaelsen. 'Non-paretic lower limb constraint with a step decreases the asymmetry of vertical forces during sit-to-stand at two seat heights in subjects with hemiparesis'. In: *Gait & posture* 32.4 (2010), pp. 457–463 (cited on page 10).
- [57] Kyung Kim, Young Mi Kim, and Dong Yeon Kang. 'Repetitive sit-to-stand training with the step-foot position on the non-paretic side, and its effects on the balance and foot pressure of chronic stroke subjects'. In: *Journal of physical therapy science* 27.8 (2015), pp. 2621–2624 (cited on page 11).
- [58] Andrew Kerr et al. 'Functional strength training and movement performance therapy produce analogous improvement in sit-to-stand early after stroke: early-phase randomised controlled trial'. In: *Physiotherapy* 103.3 (2017), pp. 259–265 (cited on page 11).
- [59] Katrine Lyders Johansen et al. 'Absolute and relative reliability of the Timed 'Up & Go'test and '30second Chair-Stand'test in hospitalised patients with stroke'. In: *PloS one* 11.10 (2016), e0165663 (cited on page 11).
- [60] Sanna E Sihvonen, Sarianna Sipilä, and Pertti A Era. 'Changes in postural balance in frail elderly women during a 4-week visual feedback training: a randomized controlled trial'. In: *Gerontology* 50.2 (2004), pp. 87–95 (cited on page 11).
- [61] Mary E Tinetti. 'Performance-oriented assessment of mobility problems in elderly patients'. In: *Journal of the American Geriatrics Society* 34.2 (1986), pp. 119–126 (cited on page 11).
- [62] Judith E Deutsch et al. 'Wii-based compared to standard of care balance and mobility rehabilitation for two individuals post-stroke'. In: *2009 virtual rehabilitation international conference. Ieee.* 2009, pp. 117–120 (cited on page 12).

- [63] Jeannette M Byrne et al. 'The effect of a three-week Wii Fit™ balance training program on dynamic balance in healthy young adults'. In: *International SportMed Journal* 13.4 (2012), pp. 170–179 (cited on page 12).
- [64] Tracy Wall et al. 'The effects of the Nintendo™ Wii Fit on gait, balance, and quality of life in individuals with incomplete spinal cord injury'. In: *The journal of spinal cord medicine* 38.6 (2015), pp. 777–783 (cited on page 12).
- [65] Heidi Sugarman et al. 'Use of the Wii Fit system for the treatment of balance problems in the elderly: A feasibility study'. In: *2009 Virtual Rehabilitation International Conference*. Ieee. 2009, pp. 111–116 (cited on page 12).
- [66] B Lange et al. 'Development of an interactive rehabilitation game using the Nintendo WiiFit Balance Board for people with neurological injury'. In: *Topics in Stroke Rehabilitation* 15.5 (2010), pp. 345–352 (cited on page 12).
- [67] Jose-Antonio Gil-Gomez et al. 'Nintendo Wii Balance board for balance disorders'. In: *2009 Virtual Rehabilitation International Conference*. IEEE. 2009, pp. 213–213 (cited on page 12).
- [68] Ross A Clark et al. 'Validity of the Microsoft Kinect for assessment of postural control'. In: *Gait & posture* 36.3 (2012), pp. 372–377 (cited on page 12).
- [69] Kenneth M Heilman, Edward Valenstein, and Robert T Watson. 'Neglect and related disorders'. In: *Seminars in neurology*. Vol. 20. 04. Copyright© 2000 by Thieme Medical Publishers, Inc., 333 Seventh Avenue, New York, NY 10001, USA. Tel.:+ 1 (212) 584-4662. 2000, pp. 463–470 (cited on page 13).
- [70] Mervi Jehkonen et al. 'Visual neglect as a predictor of functional outcome one year after stroke'. In: *Acta Neurologica Scandinavica* 101.3 (2000), pp. 195–201 (cited on page 13).
- [71] Stefano Paolucci et al. 'The role of unilateral spatial neglect in rehabilitation of right brain–damaged ischemic stroke patients: a matched comparison'. In: *Archives of physical medicine and rehabilitation* 82.6 (2001), pp. 743–749 (cited on page 13).
- [72] Tanja CW Nijboer, Boudewijn J Kollen, and Gert Kwakkel. 'Time course of visuospatial neglect early after stroke: a longitudinal cohort study'. In: *Cortex* 49.8 (2013), pp. 2021–2027 (cited on page 13).
- [73] T Schenkenberg, DC Bradford, and ET Ajax. 'Line bisection and unilateral visual neglect in patients with neurologic impairment'. In: *Neurology* 30.5 (1980), pp. 509–509 (cited on page 13).
- [74] KJ Fullerton, D McSherry, and RW Stout. 'Albert's test: a neglected test of perceptual neglect'. In: *The Lancet* 327.8478 (1986), pp. 430–432 (cited on page 13).
- [75] Magdalena Chechlac et al. 'Separating neural correlates of allocentric and egocentric neglect: distinct cortical sites and common white matter disconnections'. In: *Cognitive Neuropsychology* 27.3 (2010), pp. 277–303 (cited on page 13).
- [76] Mauro Mancuso et al. 'Italian standardization of the apples cancellation test'. In: *Neurological Sciences* 36.7 (2015), pp. 1233–1240 (cited on pages 13, 28).

- [77] P. Pullen and W. Seffens. 'Machine learning gesture analysis of yoga for exergame development'. In: *IET Cyber-Physical Systems: Theory Applications* 3.2 (2018), pp. 106–110. doi: [10.1049/iet-cps.2017.0027](https://doi.org/10.1049/iet-cps.2017.0027) (cited on page 14).
- [78] Nuno Duarte, Octavian Postolache, and Jacob Scharcanski. 'KSGphysio-Kinect serious game for physiotherapy'. In: *2014 International Conference and Exposition on Electrical and Power Engineering (EPE)*. IEEE. 2014, pp. 606–611 (cited on page 14).
- [79] Reza Haghighi Osgouei, David Soulsby, and Fernando Bello. 'An Objective Evaluation Method for Rehabilitation Exergames'. In: *2018 IEEE Games, Entertainment, Media Conference (GEM)*. IEEE. 2018, pp. 28–34 (cited on page 14).
- [80] Jung-Ying Wang and Hahn-Ming Lee. 'Recognition of human actions using motion capture data and support vector machine'. In: *2009 WRI World Congress on Software Engineering*. Vol. 1. IEEE. 2009, pp. 234–238 (cited on page 15).
- [81] Behdad Dehbandi et al. 'Using data from the Microsoft Kinect 2 to quantify upper limb behavior: a feasibility study'. In: *IEEE journal of biomedical and health informatics* 21.5 (2016), pp. 1386–1392 (cited on pages 15, 110).
- [82] Elisa Ferrara et al. 'ReMoVES Remote Monitoring Validation Engineering System: New Way of Care'. In: *Italian Forum of Ambient Assisted Living*. Springer. 2017, pp. 227–240 (cited on page 17).
- [83] Matteo Morando et al. 'Definition of motion and biophysical indicators for home-based rehabilitation through serious games'. In: *Information* 9.5 (2018), p. 105 (cited on page 17).
- [84] Matteo Morando, Marco Trombini, and Silvana Dellepiane. 'Application of SVM for Evaluation of Training Performance in Exergames for Motion Rehabilitation'. In: *Proceedings of the 2019 International Conference on Intelligent Medicine and Image Processing*. ACM. 2019, pp. 1–5 (cited on page 17).
- [85] Elise Lachat et al. 'Assessment and calibration of a RGB-D camera (kinect v2 sensor) towards a potential use for close-range 3D modeling'. In: *Remote Sensing* 7.10 (2015), pp. 13070–13097 (cited on page 19).
- [86] Daphne J Geerse, Bert H Coolen, and Melvyn Roerdink. 'Kinematic validation of a multi-Kinect v2 instrumented 10-meter walkway for quantitative gait assessments'. In: *PloS one* 10.10 (2015), e0139913 (cited on page 19).
- [87] Stefanie TL Pöhlmann et al. 'Evaluation of Kinect 3d sensor for healthcare imaging'. In: *Journal of medical and biological engineering* 36.6 (2016), pp. 857–870 (cited on page 19).
- [88] Frank Weichert et al. 'Analysis of the accuracy and robustness of the leap motion controller'. In: *Sensors* 13.5 (2013), pp. 6380–6393 (cited on page 19).
- [89] Neamah Al-Naffakh et al. 'Activity Recognition using wearable computing'. In: *Internet Technology and Secured Transactions (ICITST), 2016 11th International Conference for*. IEEE. 2016, pp. 189–195 (cited on page 20).
- [90] Martin L Albert. 'A simple test of visual neglect.' In: *Neurology* (1973) (cited on page 27).

- [91] *Stroke Engine Line Bisection test*. <https://www.strokengine.ca>. Accessed: 2018-05-18 (cited on page 27).
- [92] BF Morrey, LJ Askew, EY Chao, et al. 'A biomechanical study of normal functional elbow motion'. In: *J Bone Joint Surg Am* 63.6 (1981), pp. 872–7 (cited on page 81).
- [93] Ross A Clark et al. 'Validity and reliability of the Nintendo Wii Balance Board for assessment of standing balance'. In: *Gait & posture* 31.3 (2010), pp. 307–310 (cited on page 95).
- [94] Harrison L Bartlett, Lena H Ting, and Jeffrey T Bingham. 'Accuracy of force and center of pressure measures of the Wii Balance Board'. In: *Gait & posture* 39.1 (2014), pp. 224–228 (cited on page 95).
- [95] Sepp Hochreiter and Jürgen Schmidhuber. 'Long short-term memory'. In: *Neural computation* 9.8 (1997), pp. 1735–1780 (cited on page 107).

List of Figures

3.1	Skeleton joints tracked by the Microsoft Kinect sensor. The skeleton is composed of 3D coordinates for each of its 25 joints.	19
3.2	Skeletal tracking provided by the Leap Motion controller. Every tracked entity in the Leap Motion interaction space falls within a hierarchy that starts with the hand and ends at the individual bones.	20
3.3	The Microsoft Band 2 includes multiple sensors: optical heart rate monitor, galvanic-skin response, accelerometer, gyroscope, barometer, GPS, skin temperature sensor, and UV sensor.	21
3.4	Thumbnails of exergames in the current ReMoVES catalog.	23
3.5	Relaxation exercise: the patient inhales as the animation grows, then exhales as it shrinks.	26
3.6	a) Digital version of Albert's test included in ReMoVES platform b) Digital version of Line Bisection test included in ReMoVES platform	28
3.7	Digital version of Apple Cancellation test included in ReMoVES platform	29
3.8	Owl Nest and Shelf Cans: screenshots captured during activity designed for upper limb rehabilitation.	29
3.9	Flappy Cloud: screenshots captured during the calibration and the activity for lower limb rehabilitation.	30
3.10	Equilibrium Paint: screenshots captured during the activity. This exergame is for Sit to Stand assessment.	31
3.11	Hot Air: screenshots captured during the activity. This exergame is for load shift between lower limbs.	32
3.12	Push Box: screenshots captured during the calibration and the activity for balance control assessment.	32
3.13	PushBox exergame phases.	33
3.14	CityCar, Endless Zig and Wine Bottle: screenshots captured during the activities for hand rehabilitation.	34
3.15	Floating Trap: screenshots captured during the calibration and the activity for hand rehabilitation.	35
3.16	ReMoVES Client workflow including phases from startup to the exergame launch. .	37
3.17	"Quick Access" credentials assigned to a patient. Therapists can provide cards with the letter and color assigned to the patients, to help them to remember their credential.	39
3.18	Login phase in ReMoVES platform, based on multi-user "Quick Access" mode. .	39
3.19	MySQL relational database structure of ReMoVES platform.	43
3.20	Data flow from exergames: the raw data is sent from the client to the server with RESTful APIs and stored in the SQL database. Subsequently, a background routine takes care of processing and synthesizing the data, saving them in a dedicated field of the table dedicated to the sessions for immediate access. . . .	45

4.1	Data management flow in ReMoVES. The raw data is stored in a MySQL database and processed to provide the therapist with summarized data relating to the patient's performance. The data is mainly shown by means of graphs and indicators.	48
4.3	Plane π passing through the origin.	54
4.4	Distance d of a point P from the π plane.	55
4.5	Distance d between two parallel planes π_a, π_b .	55
4.6	The π plane halfway between π_a and π_b .	56
4.7	Classes of separable points C1, C2 and separation region for a given \mathbf{w} .	57
4.8	The orange crosses are wrong points that violate the constraints.	60
4.9	Dataset collection: the patient is performing an exergame using Microsoft Kinect as interface; the therapist interacts with a simplified interface to evaluate the patient training performance in real-time.	63
4.10	The session gets divided into segments of duration t . Each segment has a corresponding label for two-class classification: "Good" (in green) if the patient carried out the exercise correctly or "Other" (in red) if the patient performed poorly regardless of the reason.	63
4.11	Low C (a) and large C (b).	65
4.12	Large γ (a) and low γ (b).	65
4.13	General flowchart about the SVM-based method. The model is trained with the sessions carried out by the subjects. Each session is divided into segments of duration t . The "grid search" optimization process allows the tuning of the hyperparameter t .	67
4.14	Optimization of the hyperparameter t through a "grid search" process. Three examples of possible configurations. In a) and b) it is possible to identify the maximum accuracy value through the fitted line; in c) the method is not applicable as the accuracy does not seem to depend on the segment size t .	68
4.15	In the 5-fold cross-validation the dataset is divided into five groups, four for the training set and one for the test set.	68
4.16	Evaluation of a new exergame session carried out by the patient at home, without the supervision of the therapist: it is divided into segments of duration t , which are evaluated on the basis of the general SVM model (plus the patient-specific model, if available). A weighted average provides the overall evaluation.	70
4.17	Unfolded and folded scheme of RNN.	71
4.18	Long Short Term Memory (LSTM) networks is an extensions of RNN with additional hidden units used as memory.	73
5.1	(a) <i>Abduction–Adduction</i> exercise scheme; (b) <i>Hand trajectory</i> in ShelfCans game; (c) Heatmap to detect neglected areas.	81
5.2	a) Range of motion at elbow joint during flexion–extension and abduction–adduction exercise; the subject's trunk is straight. b) Undesired compensation motion in Shelf Cans exergame: lateral flexion of the trunk.	82
5.3	Plot of <i>Score–Compensation</i> and <i>Barycenter–Target position</i> features in OwlNest game. Data were labelled as "Good" or "Other" by the therapist according to patients' performance.	82

5.4	Plot of <i>Score–Compensation</i> and <i>Hand trajectory–Compensation</i> features in ShelfCans game. Data were labelled as “Good” or “Other” by the therapist according to patients’ performance.	83
5.5	Owl Nest exergame: learning curve based on patient average. On the vertical axis is measured how the game performance comes from greater experience (the horizontal axis represents the temporal sequence of exergame sessions). The game performance is defined as a percentage increase compared to the initial session.	84
5.6	Owl Nest exergame: scatter plot of the Mini-Mental State Examination score versus the maximum in-game score increase achieved by the patient, calculated as the difference between his overall best result and his first session. Each point is labeled with patient ID. The horizontal axis has the lower limit of 22 as per the inclusion criteria on MMSE.	84
5.7	Owl Nest exergame: Patient 62. The patient suffers from arthrosis of the right shoulder. The in-game score and the movement performances (such as the ROM angles) on the healthy limb (left) are better. The horizontal axes represent the temporal sequence of exergame sessions.	85
5.8	Owl Nest exergame: Patient 38. The patient fractured his right shoulder. The in-game score difference between the two upper limbs is negligible, while the extension of the left arm in all four directions is more pronounced.	85
5.9	Shelf Can exergame: Patient 62, right hand. Each point corresponds to the temporal position of the tin can on the screen: the color indicates the correct destination. The temporal evolution of the movement control is provided: in the last session the subject is more confident and delivers the tin can without much hesitation in the corresponding shelf as defined by the value distance d (lower values are better).	86
5.10	Shelf Cans exergame: Patient 62 and Patient 35. Overview of patient performance. The movement precision is calculated with distance d (lower is better): a bins for each of the three shelf positions and the bold line for the average. The horizontal dotted line indicates the standard performance of healthy subjects. The score in the game is plotted by the dot line and refers to the right vertical axis.	87
5.11	Plot of <i>Score–Compensation</i> and <i>Elevation–Compensation</i> features in the Flappy-Cloud game. Data were labelled as “Good” or “Other” by the therapist according to patients’ performance.	89
5.12	(a) Trunk tilt on sagittal and coronal planes; (b) Shoulder tilt detection.	90
5.13	Plot of <i>Repetition rate–Coronal shift</i> and <i>Repetition trend–Shoulder tilt</i> features in the EquilibriumPaint game. Data were labelled as “Good” or “Other” by the therapist according to patients’ performance.	90
5.14	Equilibrium Paint exergame: Patient 31. Lateral displacement during the game session. Spine base horizontal position.	91
5.15	Equilibrium Paint exergame: Patient 36. Shoulder angle in the coronal plane. Average angle: -3.51°	92
5.16	Equilibrium Paint exergame: Patient 52. Spine base vertical position along the first session. Long pauses and a single performed sit-up.	92

5.17 Equilibrium Paint exergame: Patient 52, spine base vertical position along the fourth session. Long pauses and limited number of sit-ups ($n = 2.5$).	92
5.18 Equilibrium Paint exergame: patient 61. Spine base vertical position along the session. Regular movement and good number of sit-ups ($n = 9$).	93
5.19 Patient 61: shoulder angle in the axial plane. Average angle: -8.07° degrees. The current game session is not the same as in Figure 5.18.	93
5.20 (a) Tracked joints for Center of Pressure (CoP) estimation; (b) Gameplay during a serious game session; (c) Erroneous balance shift detection.	94
5.21 Plot of <i>Score–CoP variation</i> and <i>CoP variation–Compensation</i> features in HotAir game. Data were labelled as “Good” or “Other” by the therapist according to patients’ performance.	95
5.22 Normalized CoP oscillation acquired both with Microsoft Kinect V2 and Wii Balance Board during a comparison test. Time is on the x -axis (2-min-long trial).	96
5.23 All the 25 joints positions of an healthy player detected from the Kinect V2 frame by frame.	98
5.24 Graph of impaired player: the periodic trend is no longer noticed.	98
5.25 Graph of impaired player: noisy and confusing data.	99
5.26 Movements detected during hand rehabilitation with Leap Motion: (a) Radial–Ulnar deviation movement in EndlessZig game; (b) Flexion–Extension movement in CityCar game; (c) Pronation–Supination movement in WineBottle game; (d) Grasping movement in FloatingTrap game.	100
5.27 Example of splitting game sessions corresponding to t and the resulting training set.	100
5.28 General scheme for construction of the dataset: therapist watches patient playing with PushBox exergame and through the web interface evaluates the patient’s performance.	101
5.29 The green zones indicate good performance and are labeled as “Good”, while the red ones are labeled as “Other”.	101
5.30 Steps from DataRawList to the definition of the dataset. Y represents the output vector, X the feature matrix (input). Y and X will be used by the SVM learning process.	103
5.31 Push Box exergame- Plot of accuracy for each iteration of the “grid search” process for t between 2.0 (extended to 0.5) and 20.0 seconds with 0.1 steps. The curve (in red) that fits the data has the global maximum in $t = 5.9$	104
5.32 Principal Component Analysis (PCA) of two components (PC1, PC3) applied to dataset obtained with segment size $t = 5.9$ seconds.	104
5.33 Shelf Cans exergame. Plot of accuracy for each iteration of the “grid search” process for t between 2.0 and 20.0 seconds with 0.1 steps. The curve (in red) that fits the data has the global maximum in $t = 8.3$	106
5.34 Sit-ups trend along the several game sessions.	107

List of Tables

3.1	Serious games list including the purpose of the activity, the employed devices, and the indicators that describe the patient performance during the exercise. . . .	26
5.1	Patients and healthy subjects in our study. General information is given in the first three columns. IDs are internal from the system Database and not necessarily in sequence (due to test, administration, or canceled accounts) The diagnosis is described in the fourth one. Fifth, sixth and seventh column contain respectively Mini-Mental State Examination (MMSE), Tinetti Index (TI) and Modified Barthel Index (MBI) values at the beginning and at the end of the hospitalization. The last three columns show the number of sessions in the database for each of the analyzed games. The total number of game sessions is 274.	77
5.2	Owl Nest exergame: scores obtained by users in the temporal sequence of exergame sessions. The patients who conducted the tests with both the right and left arm are represented in two separate rows (identified by “L” and “R” in the second column) and empty cells are used to preserve the information of the alternation between the limbs over time.	84
5.3	Sit-ups number and indices values at the beginning and at the end of the hospitalization.	94
5.4	Correlation values between sit-ups number and standard indices.	94
5.5	Push Box dataset structure: Session#ID and Segment#N are provided just for identification purpose; Evaluation defines the two target classes (Y); others are the features (X).	102
5.6	Push Box exergame: SVM performance expressed as a confusion matrix. The hyperparameter is $t = 5.9$ based on the optimization of the “grid search”. . . .	105
5.7	Shelf Cans dataset structure: Session#ID and Segment#N are provided just for identification purpose; Evaluation defines the two target classes (Y); others are the features (X).	106
5.8	Shelf Cans exergame: SVM performance expressed as a confusion matrix. . The hyperparameter is $t = 8.3$ based on the optimization of the “grid search”. . . .	107
5.9	Confusion matrix and accuracy metrics values for the classification.	108